Equity and Efficiency in the Bipartisan Infrastructure Law's Adaptation Investments

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Abstract

Public funding for adaptation to climate change may target both equity and efficiency. We evaluate adaptation funding allocated in the U.S. by the 2021 Bipartisan Infrastructure Law, which is under the equity-oriented Justice40 Initiative. We find that the funding disbursed to Census tracts increases with recent damages from climate hazards but is less clearly related to a prominent projection of future climate damages. We also find that funding does not increase in the poverty rate. Simple rules for reallocating funding to disadvantaged Census tracts may worsen the targeting of tracts exposed to climate risks, but mechanisms that target the most exposed among the disadvantaged tracts can improve both equity and efficiency. We discuss tradeoffs among different mechanisms for allocating adaptation funds. In practice, competitive grants target high-poverty Census tracts better than does discretionary spending by either state or federal governments.

1 Introduction

The United States authorized its largest investment in climate change adaptation to date through the passage of the 2021 Bipartisan Infrastructure Law (BIL). As with much public funding, adaptation funding serves many masters. Two are especially salient. First, efficiency objectives require targeting places with the greatest marginal benefit of adaptation funding. Second, equity objectives require targeting the most disadvantaged locations. The U.S. federal government mandates attention to the equity objective. In particular, the BIL is subject to the Biden administration's

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§The views expressed in this work do not represent the views of the federal government.

Justice40 Initiative, which directs 40% of the benefits of BIL funding to flow to communities deemed disadvantaged (The White House, 2021a). It is to date unclear how well adaptation funding has achieved either the efficiency or the equity objective.

We undertake a preliminary investigation of adaptation funding under the BIL. We use estimates of recent damages from climate disasters and econometrically-driven projections of losses from climate change as heuristics by which we can evaluate how the allocation of BIL adaptation funding across U.S. Census tracts accords with efficiency goals. The former is a backward-looking measure of damages and the latter is a forward-looking measure of damages. We use the close link between a Census tract's poverty rate and its qualification as "disadvantaged" under Justice40 to evaluate how the allocation of BIL funding across U.S. Census tracts accords with equity goals.

We show that the sharpness of equity-efficiency tradeoffs may depend on whether efficiency is proxied by the backward-looking or the forward-looking measure of damages. Under the forward-looking measure, disadvantaged tracts generally have less exposure to climate change damages than do non-disadvantaged tracts. Directing funds to higher poverty rate tracts worsens efficiency unless other attributes are accounted for. In contrast, under the backward-looking measure, exposure to climate risks is hump-shaped in the poverty rate: marginally disadvantaged tracts tend to have greater exposure than do non-disadvantaged tracts, and tracts with the highest poverty rates tend to have the least exposure. Directing funds to disadvantaged tracts can improve efficiency if the mechanism does not favor the most disadvantaged tracts.

We find that the funding disbursed so far under the BIL's adaptation initiatives might target efficiency but does not clearly target equity. Regarding efficiency, funding tends to be directed towards Census tracts with more recent experience of climate hazards. Funding is more ambiguously related to forecasted exposure to climate change, with a weak relationship apparent in the raw data but no relationship after controlling for state fixed effects. Regarding equity, funding tends to be directed towards Census tracts largely independently of poverty rates, not to the ones with the highest poverty rates. Only 30% of funding goes to disadvantaged tracts as a group, short of the 40% Justice40 target.

We show that simple heuristics for reallocating funds to achieve Justice40 and improve equity but reduce efficiency. We consider a uniform reallocation of funding from non-disadvantaged tracts to disadvantaged tracts in order to achieve the 40% Justice40 target. We find that a uniform reallocation of funds without considering damages tends to increase funding to tracts that are less exposed to past and future climate risks but decrease funding to tracts that are more exposed. Equity-efficiency tradeoffs appear relatively sharp at the margin under such a brute force reallocation.

Could more sophisticated funding rules soften—or even eliminate—equity-efficiency tradeoffs in reallocating funding? We find that if funding were to be reallocated to the most exposed among the disadvantaged tracts, then Justice40 targets could be achieved while also improving the targeting of tracts exposed to climate risks. Both equity and efficiency would be improved. Equity and efficiency also both improve if funds are taken only from the lowest-exposure non-disadvantaged tracts and are distributed equally amongst disadvantaged tracts, without any high-exposure targeting. Combining reallocating funds away from low-exposure non-disadvantaged tracts with reallocating funds toward high-exposure disadvantaged tracts leads to starkest change in climate risk targeting. On efficiency grounds, it is important that funding mechanisms designed to favor disadvantaged tracts be able to identify which disadvantaged tracts are more exposed to climate risks.

The BIL distributes adaptation funding through three distinct mechanisms: some funds are awarded at the federal government's discretion, some are awarded by rule-based grants to states that subsequently exercise discretion, and some are awarded by competitive application to the federal government. As we discuss below, there are, in theory, tradeoffs among these mechanisms. We estimate broadly similar correlations between each of these mechanisms and our damage measures, but we also estimate that the competitive mechanism distributes more funding to disadvantaged tracts with higher poverty rates whereas the state-controlled mechanism distributes more funding to disadvantaged tracts with smaller poverty rates.[1]

We contribute to the burgeoning environmental justice literature in economics.[2] This literature focuses on inequalities in exposure to environmental harms (e.g. Colmer et al., 2023, 2024; Bakkensen et al., 2024; Andarge et al., 2024) and on the distributional impacts of policies designed to mitigate pollutants (e.g. Sigman, 2001; Burda and Harding, 2014; Hernandez-Cortes and Meng, 2023; Currie et al., 2023; Keiser et al., 2024). Within the area of climate justice, the literature focuses on the documentation of injustice relating to climate hazards like heat or flooding (e.g. Hoffman et al., 2020; Bakkensen and Ma, 2020; Hsu et al., 2021), to the government's unequal response to climate hazards like wildfires or flooding (Billings et al., 2022; Anderson et al., 2023a,b; Jowers et al., 2023; Begley et al., 2024), to the regressivity of climate policy (Banzhaf et al., 2019; Pizer and Sexton, 2019), and to the accumulation of burdens (Bakkensen et al., 2024). We extend this literature by examining justice in the context of the allocation of funding.[3] Our analysis of U.S. adaptation funding also has relevance to international policy. International climate change

[1]Moreover, we do not find that states with environmental justice boards—bodies responsible for advising policymakers on environmental issues related to underserved communities—are more effective at targeting disadvantaged tracts.

[2]See Banzhaf et al. (2019), Banzhaf et al. (2019), and Cain et al. (2024) for recent reviews.

[3]Currier et al. (2023) study inequality in road infrastructure in the United States and find that roads are rougher in poorer and predominately Black neighborhoods. They find that road resurfacing to improve road quality is only weakly associated with road roughness. Anderson et al. (2023a) and Anderson et al. (2023b) study the allocation of wildfire risk management projects and find that projects are often awarded to communities that are wealthier, more educated, and whiter.

adaptation funds have grown severalfold in the last decade, to around \$30 billion in 2020 (OECD, 2022).[4] Notably, the BIL's \$50 billion target far surpasses the size of these funds.

In particular, we study the allocation of funds under non-binding Justice40 guidance that aims to address concerns such as those studied by the prior literature. There are few empirical papers studying the implications of environmental justice policy because there have been few examples of environmental justice policies that have such specific goals along with significant funding.[5] Prior environmental justice policy in the U.S. has typically been regulatory. The literature generally finds that regulation either fails disadvantaged groups or does not specially compensate them. Greife et al. (2017) find no relationship between local community demographics and monetary penalties leveled against corporations for violations of environmental law, even though disadvantaged communities have more violations.[6] Jenkins and Maguire (2012) study the application of solid and hazardous waste taxes and find no relationship between the tax rate and racial makeup. Although the BIL's allocation of adaptation funding falls short of the Justice40 target, we show that its funding does increase in a Census tract's poverty rate. However, this raw correlation with poverty rate vanishes once we control for other observables. Closer to our work, Hansen et al. (2021) study patterns in states' allocation of drinking water funds. We study the allocation of funds subject to a specific equity target (Justice40) and compare allocations across funding mechanisms. Concurrently with the present study, Fencl et al. (2024) show that Justice40 targets are not being met by federal funding disbursed within the state of California.[7]

We next present background on the BIL and Justice40. Subsequent sections describe data, results, and counterfactuals. We discuss funding mechanisms and avenues for future research before concluding.

2 Background

2.1 Bipartisan Infrastructure Law

The Bipartisan Infrastructure Law (BIL), also known as the Infrastructure Investment and Jobs Act, was signed into law on November 15, 2021. It provides \$1.2 trillion in investment in infrastruc-

[4] In ongoing work, we prescriptively and descriptively analyze the allocation of international climate adaptation funding to achieve equity and efficiency objectives (Lemoine et al., 2024).

[5] Prior work explores the equity implications of non-environmental federal spending programs. For instance, Boone et al. (2014) find that funding under the American Reinvestment and Recovery Act of 2009 favored districts with higher poverty rates.

[6] Campa and Muehlenbachs (2023) find that in-kind settlements of environmental court cases favor funding projects in higher-income communities.

[7] We here focus on quantitative outcomes under Justice40. Walls et al. (2024) analyze Justice40 in procedural terms.

Table 1: Adaptation programs included in this study

State Formula Programs	
-Promoting Resilient Operations for Transformative, Efficient, and Cost-saving Transportation Program (PROTECT) -Flood Mitigation Assistance Grants -Building Resilient Infrastructure & Communities	
Competitive Programs	**Federal Discretionary Programs**
-Community Wildfire Defense Grant Program For At-Risk Communities -Aquatic Ecosystem Restoration Projects -Watershed And Flood Prevention Operations -Emergency Watershed Protection Program -Water Recycling -National Coastal Resilience Fund -WaterSMART grants -Water & Groundwater Storage, And Conveyance -Tribal Climate Resilience (12 programs)	-Tribal Irrigation and Power Systems -Hazardous Fuels Management -Water-Related Infrastructure Assistance -Continuing Authorities Program -Inland Flood Risk Management Projects -Coastal Storm Risk Management, Hurricane, And Storm Damage Reduction Projects -Flood Control and Coastal Emergencies -Fuel Breaks -Southeast New England Coastal Watershed Restoration Program -Direct Spending For Resilient Recreation Sites

ture, both for new programs ($550 billion) and for existing programs ($650 billion) (UC Berkeley Labor Center, 2022).

A major aim of the BIL is to reduce climate change damages through infrastructure investment. The BIL was immediately subject to the Biden Administration's Justice40 initiative (described below). Moreover, President Biden issued Executive Order 14052 on the same day that the BIL was signed. This executive order requires federal agencies to prioritize "building infrastructure that is resilient and that helps combat the crisis of climate change" and confirms the BIL's placement under the President's Justice40 Initiative (The White House, 2021b).

Over 100 programs in the BIL, across eight federal departments, explicitly allocate funds to climate resilience. Some of the largest programs are PROTECT (Promoting Resilient Operations for Transformative, Efficient, and Cost-Saving Transportation – $8.7 billion), the Grid Resilience Program ($5 billion), Flood Mitigation Assistance grants ($3.5 billion), and the Coastal Storm Risk Management Projects ($2.5 billion). The White House estimates that $50 billion dollars in the BIL are dedicated to climate resilience (The White House, 2022).

We study a subset of the adaptation programs in BIL, accounting for $10.1 billion in funding. Table 1 lists the 32 programs we study. We categorize projects as adaptation programs based on labels in the data and on descriptions of funding provided by federal agencies (Federal Emergency Management Administration, 2020; Federal Highway Administration, 2022). We classify these adaptation programs into three groups depending on the mechanism through which funding is awarded. Section A in the appendix describes one program from each group in more detail.

The first set of projects is funded through competitive grants. Competitive grants cover the widest variety of programs, including desalination plants, watershed protection, and tribal relocation. These grants are often available to states and to local governments and organizations. Notices of funding for these grants are publicly announced. The applications are reviewed and chosen by the agency that runs the grant program. The federal government is aware of the institutional capacity required to apply for competitive grants and has attempted to make this funding type more available to disadvantaged communities through rolling deadlines and technical assistance funding (The White House, 2024b; Walls et al., 2024). In total, \$1.32 billion was allocated through competitive grants to projects in our dataset, accounting for 13% of the total funding.

The second set of projects is funded through formula grants to states. Some of these grants are automatically distributed to states (in PROTECT). Others are available upon states' request, up to a fixed cap (in Building Resilient Infrastructure and Communities) or up to a percentage of previously allocated federal disaster dollars (in Flood Mitigation Assistance Grants[8]) (Federal Emergency Management Administration, 2020; Federal Highway Administration, 2022). The funding must be used within program guidelines, but the federal government otherwise has little control over how formula funding is used after it is given to states.[9] Funds distributed via state formula to projects in our dataset total \$1.92 billion, which is 19% of total funding.

The last set of projects is funded by the federal government on a discretionary basis. These tend to be directly administered by federal agencies, although often in consultation with local communities. Federal discretionary funding is the largest of the three funding mechanisms with \$6.81 billion in funding allocated to projects in our dataset, accounting for 68% of total funding.

2.2 Justice40

Justice40 is a federal initiative to direct 40% of the benefits of climate, clean energy, affordable and sustainable housing, clean water, and other investments to disadvantaged communities. Justice40 was established under Executive Order 14008, titled "Tackling the Climate Crisis at Home and Abroad" and signed in the first week of the Biden presidency (The White House, 2021a). Unlike

[8]Our main dataset denotes Flood Mitigation Assistance Grants as "formula" even though FEMA considers them competitive. This may be because the program is actually the closely-related "Hazard Mitigation Assistance" program which functions as described above, or because only states can compete for Flood Mitigation Assistance. In either case, the state is the entity that receives money and then distributes the money.

[9]Boone et al. (2014) discuss formula funding in the American Reinvestment and Recovery Act of 2009.

previous national environmental justice initiatives, Justice40 applies comprehensively across departments and includes specific goals and guidance (Mueller and Lilley, 2022). Although Justice40 is not binding, departments are required to report their methods and outcomes in reaching the goal (Young et al., 2021). Because climate adaptation is a specific focus of Justice40, virtually all of the projects we consider are subject to Justice40.

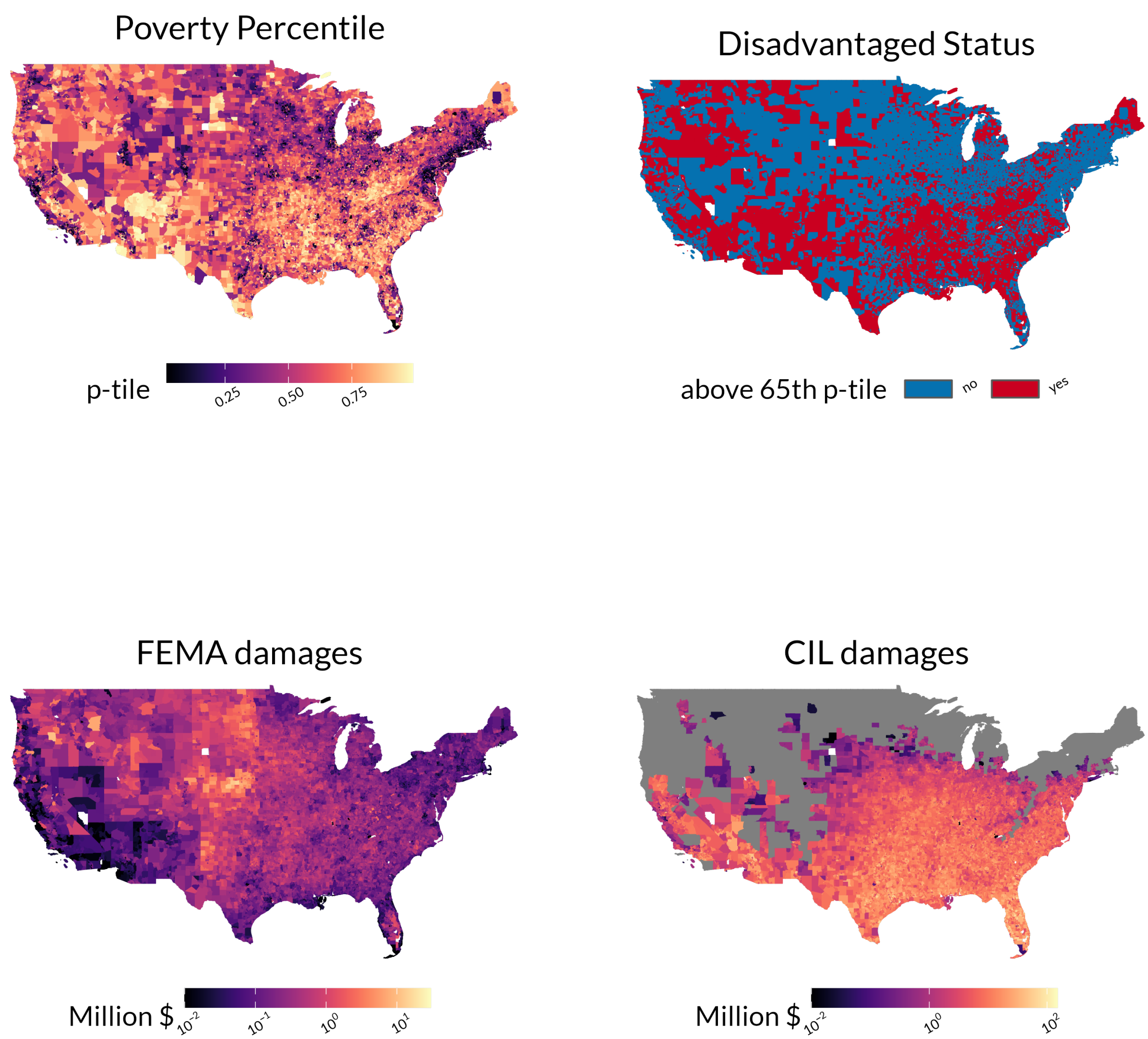
Census tracts are defined as "disadvantaged" under a standard metric, which is publicly displayed through the Climate and Economic Justice Screening Tool (Council on Environmental Quality, 2023). Tracts are considered disadvantaged if (i) their share of households below 200% of the poverty line is at or above the 65th percentile and (ii) they qualify as disadvantaged in one other category of climate, energy, health, housing, legacy pollution, transportation, water/wastewater infrastructure, or workforce development. The latter "burden" thresholds are quantitatively defined. There are some rules that allow tracts below the 65th percentile of poverty rate to qualify as disadvantaged (for instance, if they are surrounded by other disadvantaged tracts and are above the 50th percentile of poverty rate). Figure C5 in the appendix shows that little adaptation funding flows to disadvantaged Census tracts below the 65th percentile poverty rate threshold. In total, 94% of tracts above the 65th percentile of poverty rate qualify as disadvantaged, whereas only 11% of tracts below the 65th percentile are considered disadvantaged. Given this close mapping between a Census tract's disadvantaged status and whether it is above the 65th percentile of poverty rate, we will often collapse "disadvantaged" status to its poverty rate dimension. Doing so permits graphical and quantitative analyses of a continuous measure that closely proxies disadvantaged status.

There are several challenges in evaluating Justice40. First, the initiative requires 40% of "benefits", rather than 40% of "funding", to flow to disadvantaged communities. Benefits are harder to measure (see Walls et al., 2024), so we follow recommendations in White House Environmental Justice Advisory Council (2022) by focusing on funding.[10] Second, for most programs, the government does not yet have the ability to track exactly where funding flows. As described in Section 3.2 below, we try a few reasonable approximations to how funding may be distributed. Third, the Census tract-level disadvantaged measure may be too coarse to target disadvantaged communities, especially for geographically large Census tracts (Walls et al., 2024). We conduct our analysis at the Census tract level but acknowledge that there may be important variation within tracts.

The top two panels of Figure 1 plot, for each Census tract, its poverty rate percentile and whether it is above the 65th percentile poverty rate threshold for being considered disadvantaged. Disadvantaged tracts tend to be located in the South and West.

[10] White House Environmental Justice Advisory Council (2022) argues that the flow of funding itself directly benefits disadvantaged communities, beyond the resilience and other benefits procured by the funding.

Figure 1: Census-tract level data on poverty, disadvantaged status, and damages.



Note: The top left panel maps each Census tract's percentile in the distribution of the share of households below 200% of the poverty line. The top right panel plots whether a Census tract is above the 65th percentile poverty rate, which is the criterion for being considered "disadvantaged" on the poverty measure. The bottom left panel plots each Census tract's expected annual loss from climate hazards according to the FEMA National Risk Index. The bottom right panel plots each Census tract's projected median damages to agriculture, mortality, energy, labor, crime, and coastal hazards under RCP 8.5 between 2080–2099 from the CIL. Gray areas for CIL damages are locations projected to have benefits in 2080–2099 under RCP 8.5.

3 Data

3.1 Census Tracts and Demographics

Our data come from the U.S. government's Climate and Economic Justice Screening Tool, which is a public map of disadvantaged status (and therefore eligibility for Justice40 funding) assigned to 2010 Census tracts. This map includes data on the components that go into disadvantaged status, including the percentile of poverty rate (Council on Environmental Quality, 2023), and also demographic information like population.[11] There are 72,739 Census tracts in the U.S.: 36.3% of them are considered disadvantaged, and these include 32.7% of the population of the U.S. Therefore, Justice40 will be met if, on average, $1.17 flows into disadvantaged tracts for each $1 into non-disadvantaged tracts. Other demographic variables (e.g., race and per capita income) and tract characteristics (e.g., rural percentage) come from the National Historical Geographic Information System on IPUMS (Manson et al., 2023). To match the government's BIL map, we use the most recent data which are assigned to the 2010 tract boundaries.

3.2 Adaptation Funding

Our main source of adaptation project data is Invest.gov (The White House, 2024a). To the best of our knowledge, this is the most complete source of BIL projects that is categorized by program and funding type. We categorize projects that are labeled "resilience" and pertain to the environment (as well as some water projects[12]) as adaptation funding. Nevertheless, some programs and projects are omitted from Invest.gov, as are some award amounts and most geographic information. When city names and counties are provided, we attach the relevant shapefiles. When we have both city and county information, we keep the smaller unit. When we cannot match to cities, we use information from the project description, which often describes natural landmarks, neighborhoods, and towns where projects take place. We geolocate this information using the Google Maps API. In order to avoid assigning all funding to tracts at, for instance, town centroids, we approximate the area of a project by drawing a 10 kilometer buffer around its geolocated point. We then assign funding to Census tracts in two different ways: (1) weighted by a Census tract's area within the buffer, and (2) weighted by a Census tract's population within the buffer.

The universe of BIL awards is available through Spending.gov's infrastructure spending data tables (USASpending, 2024). We use these data for the PROTECT formula program because they

[11]Population is from the 2015-2019 American Communities Survey data. These are the most recent data that correspond perfectly to the 2010 Census tracts.

[12]For example, projects relating to irrigation efficiency enhancement, aquifer storage, groundwater well drilling, drought resistant landscaping, and canal enclosure, all of which are intended to improve economic or welfare outcomes under water scarcity.

are more complete and better assigned to location than the Invest.gov data.[13]

Finally, we collect tribal climate adaptation awards from the Bureau of Indian Affairs (since many of these awards are missing in the Invest.gov data). We attach these awards to reservation geometries, as they are awarded to tribes on specific lands (Bureau of Indian Affairs, 2024).

In total, we observe 2,100 BIL adaptation projects funded between January 2022 and January 2024. Figure 2 shows county-level aggregations of our BIL project data. Funding tends to be concentrated in the West and along the coasts.[14]

A handful of tracts are significant outliers in terms of funding. For example, the Census tract receiving the most funding receives nearly 500 times more funds than the Census tract at the 99.5th percentile. To ensure that our results are not driven by a handful of extremely large projects, we winsorize the funding variable at the 99.5th percentile. Appendices B and C assess sensitivity to buffer size, population-weighting, and winsorization threshold.

We choose to study the distribution of total rather than per-capita adaptation funding for two reasons. First, using total funding coheres with Justice40, which is concerned with benefits flowing to tracts (communities) rather than individuals. Second, studying total funding is also consistent with the adaptation projects that we study being used to public goods, such as resilient transportation infrastructure, flood prevention, wildfire prevention, and ecosystem resilience. In such cases, a given household's benefit may scale with total funding rather than funding per capita. For example, a wildfire prevention program will result in better air quality, lower fire risk, and improved access to natural lands for all households in the targeted tract.[15] Appendix D shows that our primary results are similar whether studying total or per capita funding.

Whether projects have public or private benefits does affect the interpretation of the funding distribution. Appendix C shows that the highest poverty rate Census tracts tend to have the smallest populations.[16] Funding per capita will therefore mechanically appear more progressive than total funding. But if what matters is how many people enjoy the creation of a public good, then ignoring the fact that the highest poverty rate Census tracts contain fewer people may lead us to overstate the progressivity of adaptation funding.

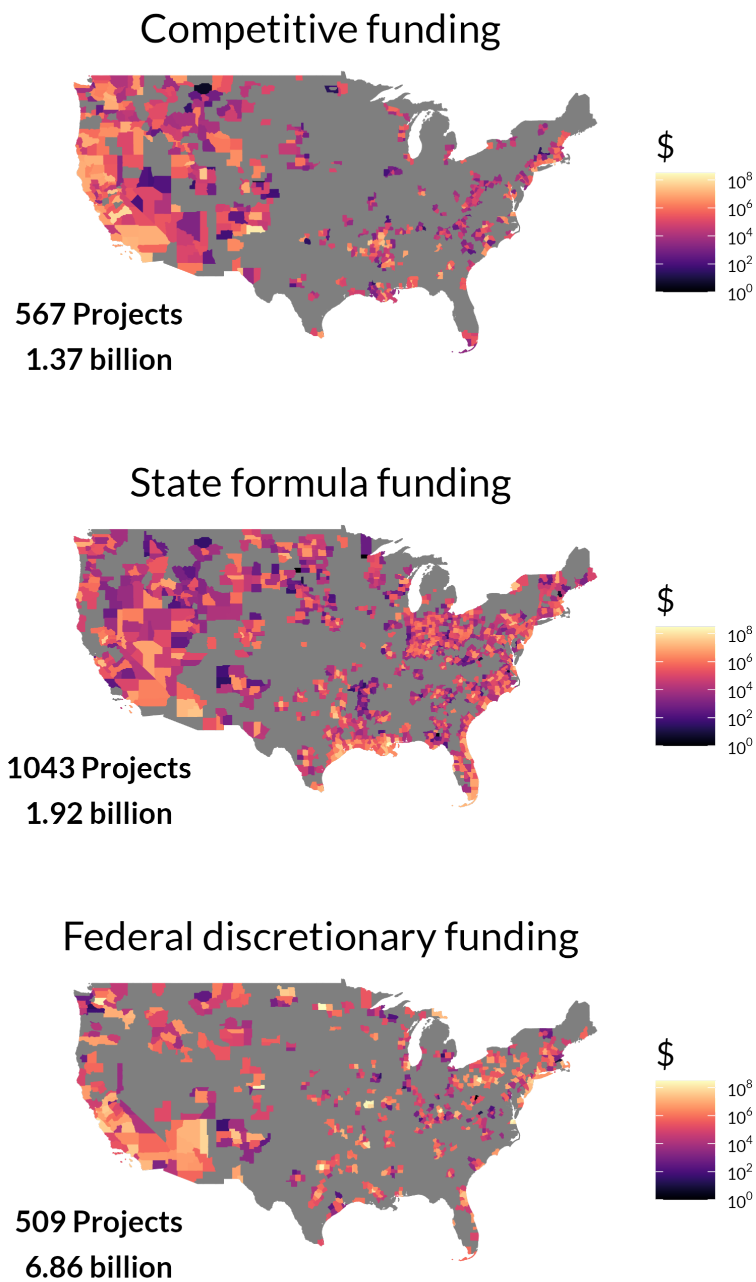
[13]Apart from PROTECT, the BIL awards in Spending.gov do not have consistent program labels, which make them difficult to classify as "adaptation spending" or not.

[14]The largest projects in our sample are completed directly by federal agencies, which include the Army Corps of Engineers' flooding prevention infrastructure (US Army Corps of Engineers, 2024) and fire hazard reduction programs administered by the Forest Service.

[15]If projects were, instead, privately beneficial, then each household would receive only the fraction of total funding spent specifically on their household. An example is the BIL's Weatherization Assistance Program, which funds improvements to the homes of low-income families for energy efficiency. However, we do not include that program in our study because it targets current energy burden rather than future climate resilience.

[16]The tracts with the highest poverty rates tend to be in inner cities. These tracts rend to have small populations because Census tracts were drawn to make demographics, economic status, and living conditions fairly homogeneous.

Figure 2: County-level maps of adaptation funding, area weighted



3.3 Voting

We obtain voter turnout and percent voting for Joe Biden and Donald Trump in 2020 at the precinct level from the Voting and Election Science Team (Voting and Election Science Team, 2020). We aggregate the data to the Census tract level.

3.4 Climate and Damages

For projected climate, we use the SSP2-4.5 emissions scenario from a group of nine Coupled Model Intercomparison Project Phase 6 (CMIP6) models disaggregated to a 1 kilometer resolution over North America, compiled by the AdaptWest Project (Mahony et al., 2022). The AdaptWest project also provides our baseline climate measure, which is average temperature between 1990 and 2020.

We use two measures of climate damages. The first is from FEMA's National Risk Index database.[17] We sum the expected annual losses for six of the climate hazards in the data that scientists generally expect to increase with climate change (coastal flooding, drought, heat, hurricanes, riverine flooding, and fires).[18] The expected annual loss is defined as the historical loss ratio,[19] multiplied by the historical annualized frequency of hazards, multiplied by the value of buildings, agriculture, and population exposed to the disaster. Therefore the FEMA measure is a backward-looking measure that proxies current climate risk by recent experience of climate disasters.

The second measure of damages is county-level projections for median damages relating to agricultural yields, mortality, energy expenditures, labor supply, crime, and coast-specific hazards over 2080–2099 under RCP 8.5, estimated in Hsiang et al. (2017) for the Climate Impact Lab (CIL). These projections are constructed from estimated relationships between each damage category and weather. The CIL measure is a forward-looking measure that is a proxy for future climate risk. In terms of levels, the CIL measure is likely to overestimate climate risk for our application: RCP 8.5 is likely to overestimate warming, and the 2080–2099 prediction is farther out than the 30-year horizon of many infrastructure investments. However, the geographic patterns of damages are likely to be similar between mid-century and end-of-century warming and across various warming

[17] `https://hazards.fema.gov/nri/`

[18] We omit losses from three hazards (earthquakes, tsunamis, and volcanic eruptions) that are, barring scientific breakthroughs linking plate tectonics to ice sheet loss, clearly unaffected by climate change. We also omit losses from hazards that are either expected to decrease with climate change or have an uncertain relation to climate change (cold waves, hail, ice storms, lightning, wind, winter weather, avalanches, and landslides). Such hazards are not explicitly targeted by adaptation projects in our data. We also omit losses from tornadoes, for similar reasons and also because they tend to dominate the loss metric (their losses are very large relative to losses from other hazards). We explore the association of a broader set of disasters with BIL funding in the appendix.

[19] The percentage of buildings, agriculture, and people expected to be lost during a disaster is estimated from historical data in the Spatial Hazard Events and Losses Database.

trajectories, so the cross-sectional correlations of interest here should be valid.

The CIL estimates are reported as percentages of county income. However, the original CIL damage estimates do not depend on income: their damage functions relating temperature to outcomes are the same for all counties, irrespective of income. They divide their estimated losses by income and thereby mechanically relate their reported losses to income. To remove the mechanical relationship with income and make the CIL measure comparable to the FEMA measure, we multiply the county-level CIL metrics by tract-level population and per capita income.[20]

The bottom two panels of Figure 1 plot our two damage measures. Gray areas on the CIL map correspond to places projected to benefit from climate change. The CIL damage measure shows a clear north-south gradient whereas the FEMA damage measure does not.

3.5 State Environmental Justice Oversight Boards

Our list of states with environmental justice boards comes from the National Conference of State Legislatures.[21] 14 states have environmental justice boards, and 6 of them have been established since 2021. States with environmental justice boards tend to be large: 46% of tracts in the data reside in a state with an environmental justice board.

4 Results

We first describe the relationships between climate adaptation funding, poverty, and climate risk. We then estimate the determinants of funding.

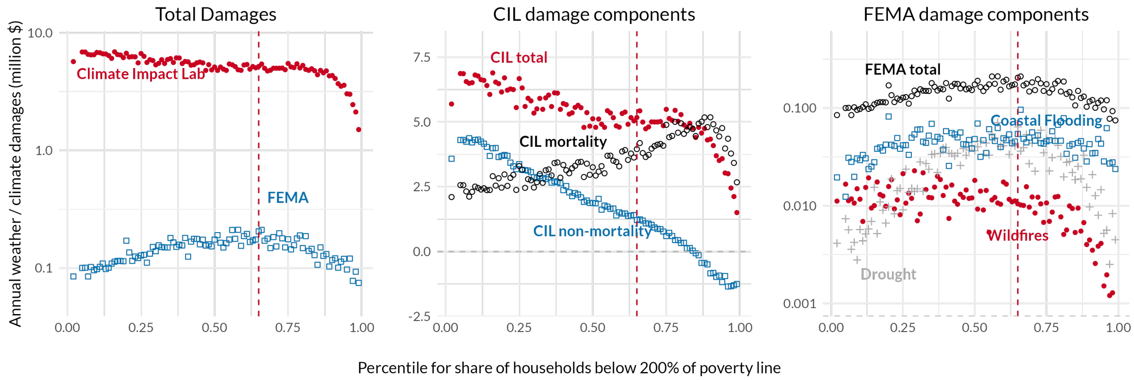
4.1 Potential for Equity-Efficiency Tension

The correlation between a location's climate risk and its poverty rate determines the sharpness of any tradeoff between achieving the BIL's stated equity goals and efficiently allocating its funds to minimize climate damage. If the most impoverished locations are also those with the greatest climate risk, then it may be possible to achieve significant climate risk reductions while directing funds to meet non-climate equity objectives. However if the wealthiest locations are those at greatest climate risk, then there may be more tension between achieving the greatest aggregate benefit from adaptation investments and achieving non-climate equity objectives.

[20]The CIL measure will retain some direct income dependence based on, for instance, coastal damages depending on the capital stock and the labor valuation using state-level value-added. However, mortality is the largest component of the CIL index and does not directly depend on income, as the CIL measure uses a constant value of statistical life.

[21]https://www.ncsl.org/environment-and-natural-resources/state-and-federal-environmental-justice-efforts

Figure 3: Average damages by poverty rate share percentile



Note: The left panel plots a binscatter of annual climate damages (in million $) for our two damage measures, against each percentile of the Census tract distribution for the share of households below 200% of the poverty line. The FEMA measure is a sum of the annual losses of six climate-related disasters, and represents current expectations of weather-related hazards, whereas the CIL measure shows expectations of future (2080–2090) damages in a high emissions scenario. The center plot separates the CIL measure into mortality and non-mortality components, while the rightmost plot shows the aggregate FEMA measure, as well as three of the six damage categories in the FEMA measure.

Figure 3 plots our two measures of climate risk against the share of a Census tract's households below 200% of the poverty line, which is the Justice40 measure of poverty rate. This plot is a binscatter, in which each point corresponds to a poverty rate percentile (horizontal axis). The level of each point along the vertical axis denotes average damages across Census tracts conditional on being in that percentile, on a log scale for plotting. The points therefore tell us how directing funding to the average Census tract from that percentile poverty rate matches damages under each metric. The vertical dashed line corresponds to the 65th percentile, which is a threshold used to define disadvantaged tracts for the Justice40 initiative (see Section 2.2).

Both measures of climate risk tend to project the least damages in the tracts with the highest poverty rates (left panel). The damage binscatter is monotonically decreasing in the CIL measure, but is hump-shaped in the FEMA measure. On average, the FEMA measure projects slightly more[22] damage in disadvantaged Census tracts above the 65th percentile cutoff compared to those below the cutoff.

The middle panel considers the components of the CIL index. The most important component of the CIL index is mortality damages, which do not directly depend on income (see footnote 20). The observed decline in mortality damages at the highest poverty rates may partly pick up where the rich and poor tend to live within the U.S. The sharp decline in CIL non-mortality damages

[22] $0.14 million for non-disadvantaged vs $0.145 million for disadvantaged.

in the poverty rate may reflect differing exposure to coastal risks and differing capital stocks. The right panel shows that climate risk declines in the poverty rate most sharply for the wildfire component of the FEMA damage metric and has an especially pronounced hump-shape for the drought component of the FEMA damage metric.

If climate damage risk reflects the benefit from publicly funded adaptation investments,[23] and if poverty rate captures equity objectives,[24] then we can interpret Figure 3 as describing whether equity-efficiency tradeoffs are sharp. Here we see that the choice of damage measure matters. The equity-efficiency tradeoff is clear—and is potentially sharp—if we take forward-looking CIL damages as a measure of where efficient adaptation spending should concentrate. To reconcile efficiency and equity, funding agencies must be careful to select the most exposed among the disadvantaged tracts. In contrast, the equity-efficiency tradeoff may not be substantial if we take backward-looking FEMA damages as a measure of where efficient adaptation spending should concentrate. In that case, federal agencies will, on average, advance efficiency goals by reallocating funding towards disadvantaged tracts around the threshold, even without considering the climate risk exposure of the targeted tracts.

4.2 The Raw Relationship Between Funding and Poverty

We now describe the raw association between adaptation funding and poverty rate, again measured as the share of a Census tract's households below 200% of the poverty line. Figure 4 binscatters this relationship for each funding mechanism. As before, each point averages over its corresponding percentile.

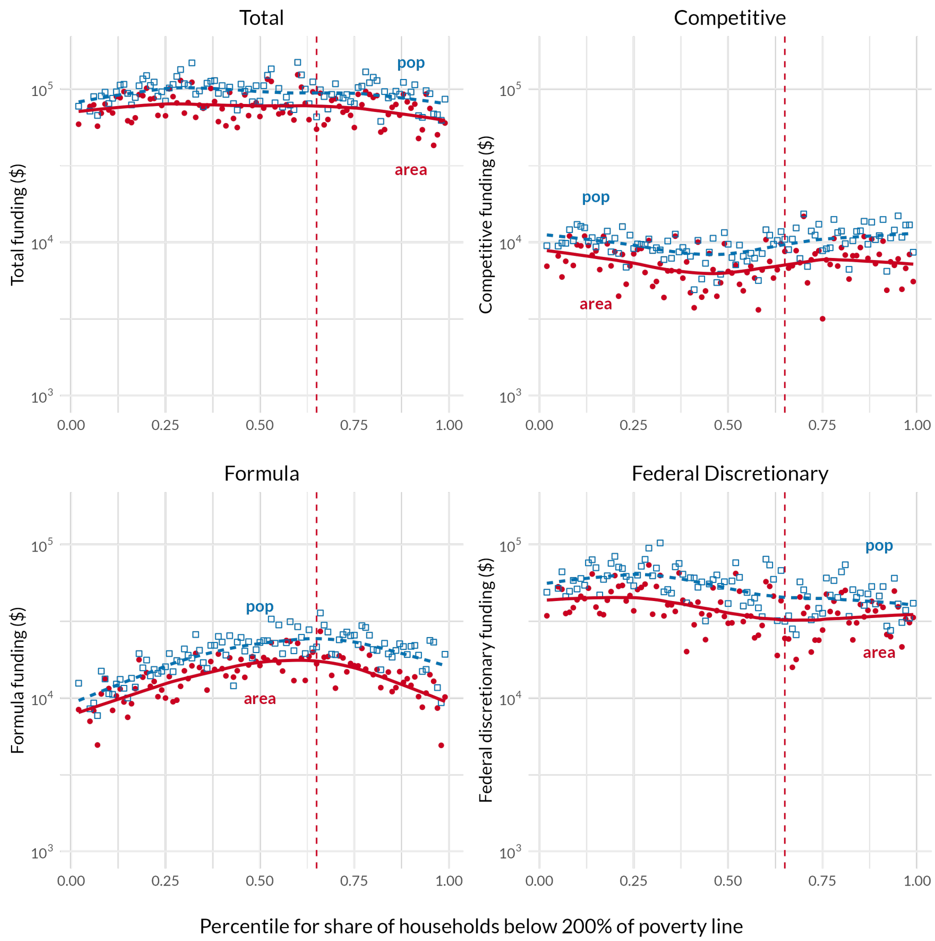
The solid points and line assign funding to Census tracts in proportion to their area within the 10km buffer, and the hollow points and dashed line assign funding in proportion to population. In either case, adaptation funding has a fairly flat relation to poverty rate, without a clear change at the 65th percentile cutoff used to define disadvantaged tracts. Among disadvantaged tracts, the least disadvantaged receive slightly more funding on average.

The three funding mechanisms show different funding-poverty rate relationships. State formula funding has a hump-shaped relation to poverty rate, with funding peaking around the 65th percentile cutoff before slightly declining. Competitively allocated funding has the opposite relationship, decreasing in poverty rate until around the median Census tract and increasing in poverty rate after that. Federal discretionary funding does not show a clear pattern. If anything, it is weakly

[23]The benefit from additional adaptation spending in fact also depends on the efficacy of adaptation spending at offsetting climate risk and on how public spending interacts with private spending.

[24]Poverty rate is the primary criterion for classifying a tract as disadvantaged under Justice40. In a distinct context, Hansen et al. (2021) recommend using poverty rate as the metric for assessing equity when distributing drinking water funds.

Figure 4: Adaptation funding, by poverty rate percentile and funding mechanism



Note: Each point is the average funding for each percentile of the Census tract distribution of the share of households below 200% of the poverty line. Before taking the average we winsorize Census tract funding levels to the 99.5th percentile. The solid lines are locally estimated best-fit lines for funding assumed to be distributed equally over area; the dashed lines are the analogous best-fit line for population-weighted funding. The vertical dashed line corresponds to the 65th percentile, which is the threshold for meeting the poverty rate criterion for being considered disadvantaged.

decreasing in poverty rate.

Figure 5 depicts how different states allocate their formula funding, which is distributed within states by state-level decision-makers. This figure assigns funding by area within a 10 kilometer radius (Appendix Figure C7 shows results of allocating by population). In many states, there is not a clear relationship between formula funding and poverty rate. But in some states, formula funding either has a hump shape or is decreasing in the poverty rate percentile, so that the disadvantaged tracts with lower poverty rates receive more funding than the disadvantaged tracts with higher poverty rates.[25]

Table 2 reports the share of funding going to disadvantaged tracts in our sample of adaptation projects, using the full Justice40 definition of "disadvantaged" rather than just the poverty rate dimension. The Justice40 target is for 40% of the benefits to flow to these tracts.[26] Regardless of whether we assign funding to locations by population or by area, only around 30% of the funding is directed towards disadvantaged tracts.[27] However, there is significant heterogeneity across funding mechanisms. Over half of the competitive funding flows to disadvantaged tracts, whereas only around a quarter of the federal discretionary funding—which the federal government has the most direct control over—goes to disadvantaged tracts. State formula funding approximately hits the Justice40 target. Surprisingly, states with EJ boards tend to have a smaller share of funding going to disadvantaged Census tracts than those without.[28] This fact does not imply that EJ boards worsen equity objectives. Instead, states' decisions to form EJ boards could reflect circumstances that complicate funding disadvantaged tracts.

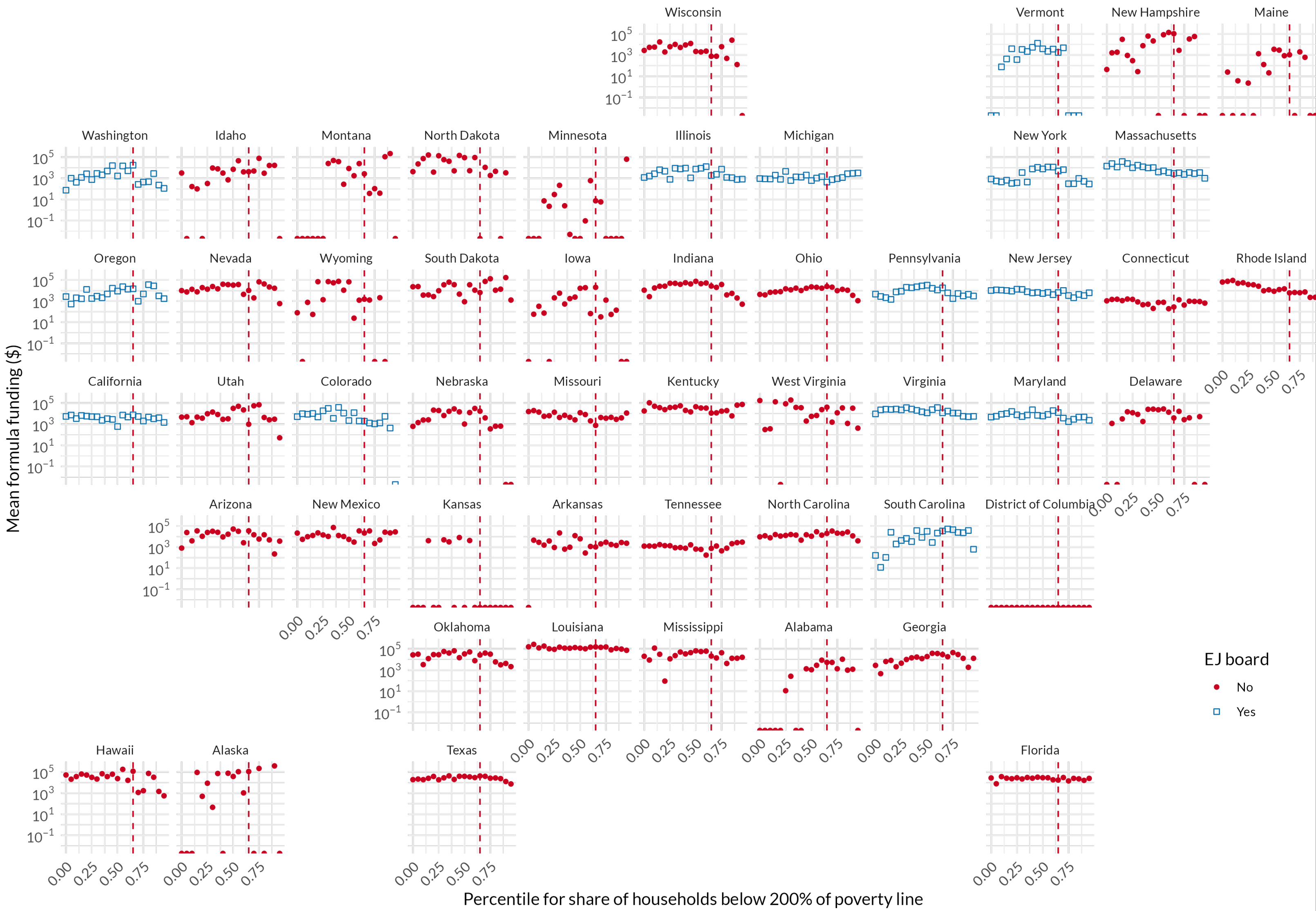
[25] There are a handful of exceptions, such as Michigan and Tennessee.

[26] Note that not all disadvantaged tracts are above the 65th percentile of the poverty distribution, as described in Section 2.2. However, Figure C5 in the appendix shows that little funding flows to disadvantaged Census tracts below this threshold.

[27] Appendix B.1 assesses sensitivity to the radius used to assign funding to nearby tracts. It shows that the combination of a very small radius with a rule that allocates by population can just meet the Justice40 target but that other combinations fall short. The shortfall tends to increase with the assumed radius.

[28] 40% of tracts in states without EJ boards are disadvantaged, compared to 28% of tracts in states with EJ boards. Neither type of state meets the requirement of $1.16 to disadvantaged tracts for every $1 to non-disadvantaged tracts. Non-EJ board states achieve $0.81 on the dollar. EJ board states achieve only $0.59 to every dollar.

Figure 5: Formula funding for tracts in each poverty bin, area weighted



Note: Each point is the average state formula funding for each percentile of the Census tract distribution of the share of households below 200% of the poverty line, for each state. Before taking the average we winsorize Census tract funding levels to the 99.5th percentile. The vertical dashed line corresponds to the 65th percentile which is the threshold for meeting the poverty rate criterion for being considered disadvantaged. Blue squares denote states that have environmental justice boards and red dots denote states that do not. Binscatter percentiles are calculated using the national poverty rate share distribution. Zero values indicate either no funding was allocated to Census tracts with that poverty rate percentile or that the state does not have any Census tracts falling into that poverty rate percentile.

Table 2: Fraction of funding going to disadvantaged tracts, by funding mechanism

	Competitive	Discretionary	Formula	Total
All states				
Area-weighted	0.52	0.23	0.36	0.29
Population-weighted	0.53	0.25	0.42	0.32
States with EJ boards				
Area-weighted	0.32	0.19	0.29	0.22
Population-weighted	0.34	0.24	0.29	0.26

4.3 The Raw Relationship Between Funding and Climate Risk

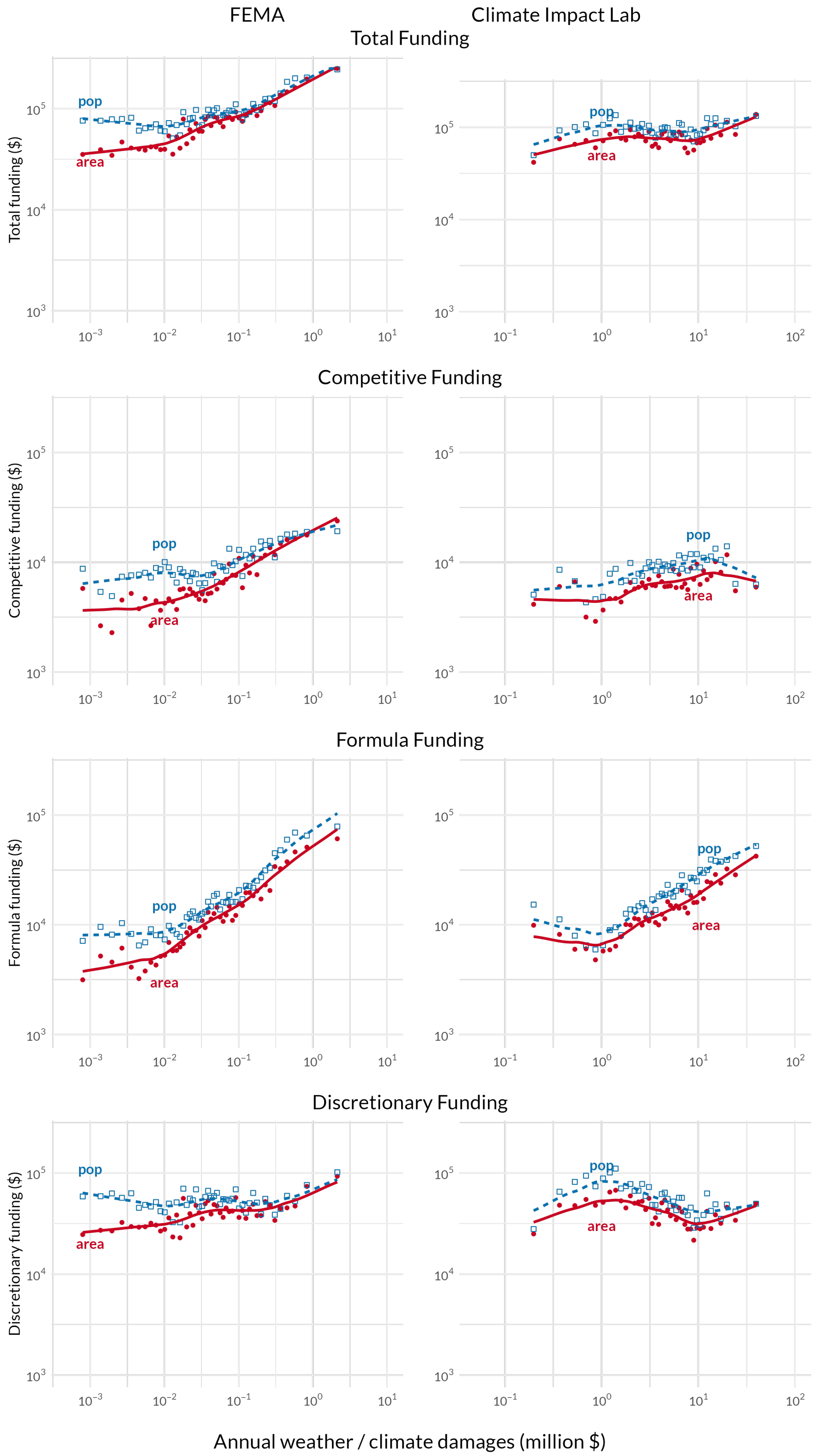
We now assess the raw relationship between adaptation funding and climate risk. Figure 6 plots funding against FEMA damages and CIL damages as binscatters. By either damage measure, more funding is allocated to the Census tracts that are more exposed to climate change. All three funding mechanisms appear to target FEMA damages. Formula funding appears especially well-targeted to CIL damages, whereas discretionary funding appears uncorrelated or even negatively correlated with CIL damages.

4.4 Determinants of Funding

We next statistically explore which factors determine the allocation of funding. Infrastructure variables (building value and highway length) measure assets that may need to be protected from climate change and also measure the availability of targets for PROTECT projects, among others. The percentage of a tract's area that is rural, the percentage of a tract's population that is white, and the tract's population and area capture geographic and demographic factors that could influence the allocation of funding. We proxy for electoral incentives with voter turnout share and the percentage of the tract voting for Biden in the 2020 presidential election. We proxy for climate risk with average temperature over 1991–2020, expected temperature change from 2020 to 2050 (a relevant time period for infrastructure investment), and the two (log) measures of damage risk described above. We also include an indicator for whether a county is coastal, which affects both infrastructure needs and climate risk.[29]

[29] The coastal indicator may be correlated with the FEMA and CIL damage measures, as both explicitly include coastal damages. We find that including or excluding the coastal indicator in the regression has little effect on our other coefficient estimates, including the damage coefficients.

Figure 6: Funding mechanisms by damage components



Note: Each point is the the average Census tract funding plotted against FEMA and CIL damages. Before taking the average we winsorize Census tract funding levels to the 99.5th percentile. The FEMA measures represents current expectations of weather-related hazards for six climate-related disasters. The CIL measure represents one version of expected future (2080–2090) damages in a high-emission scenario. For the lowest damage percentiles, the CIL measure estimates no damages, or negative (cold states are better off under climate change). We exclude these lowest bins from the plot to allow for a log scale. The solid lines are locally estimated best-fit lines for area-weighted funding; the dashed lines are the analogous best-fit line for population-weighted funding.

Our estimates of each factor's association with funding should not be read as causal. Each association is identified by how funding is allocated among the Census tracts within a state. However, there is no shortage of other potential determinants of funding that could correlate with poverty rate, disadvantaged status, or any other covariate. Therefore one should not read our results as predicting how manipulating a given factor would affect funding. Instead, we describe the correlation between each factor and observed funding flows, net of the other factors included in the regression.

Our estimating equation is

$$y^j_{is} = \alpha^j_1 P_{is} + \alpha^j_2 D_{is} + \alpha^j_3 (P_{is} - 0.65) D_{is} + \beta^j X_{is} + \eta^j_s + \epsilon^j_{is}, \tag{1}$$

where i indexes Census tracts, s indexes states, and j indicates the type of funding mechanism (competitive, formula, discretionary, or all mechanisms jointly). y^j_{is} is funding issued via mechanism j to tract i in state s. P_{is} is the percentile rank of Census tract i's poverty rate. We again follow the Justice40 criteria in measuring poverty relative to 200% of the poverty line. The D_{is} are indicators for whether a tract is disadvantaged in the sense of being above the 65th percentile poverty rate threshold. Its interaction with poverty rate permits tracts below the threshold to have a different relation to the poverty rate than do tracts above the threshold. The coefficients α^j are to be estimated. α^j_1 tells us how funding changes in poverty among the non-disadvantaged tracts, α^j_2 tells us how funding changes as we cross the 65th percentile poverty rate threshold, and α^j_3 tells us how the slope between funding and poverty rate differs for tracts above the threshold.[30]

The vector X_{is} contains the covariates described above, with coefficient vector β^j to be estimated. The η^j_s are state fixed effects. We cluster standard errors at the state level to account for correlation among unobservables across a state's Census tracts, which could be driven by how states choose to distribute the funding or by states advising the federal government about projects to fund, among other possibilities.

We estimate equation (1) separately by mechanism j. One challenge with estimating equation (1) is that 60% of our Census tract-funding mechanism-level observations receive zero funding. To handle this large share of zeros, we estimate equation (1) using Poisson Pseudo Maximum Likelihood.[31]

Table 3 shows the results for the main coefficients of interest of the descriptive regressions, and figure 7 shows the coefficients on the controls in the full regression, for each funding mechanism and

[30]The slope of funding in poverty rate above the threshold is $\alpha^j_1 + \alpha^j_3$.

[31]Poisson Pseudo Maximum Likelihood does not impose distributional assumptions on the outcome variable and circumvents the use of arbitrary transformations of the outcome variable, such as $\log(y + 1)$ or $\text{asinh}(y)$, that are not scale-invariant.

both assumptions about funding weighting. The top two panels of Table 3 reports estimates of the association of funding with poverty rate percentile, allowing the association to vary depending on whether the Census tract is above or below the threshold for meeting the disadvantaged criterion. These estimates are piecewise linear versions of the results shown in Figure 4, except conditioned on state fixed effects.

The first column reports estimates for the total pool of funding. The point estimates suggest that funding increases with poverty rate percentile among non-disadvantaged tracts, jumps down at the 65th percentile threshold, and, summing the first and third rows, falls in poverty rate among disadvantaged tracts. None of these estimates are statistically significant. Funding is not consistently related to the poverty rate.

We find that individual funding mechanisms can display different results. The pattern for total funding appears driven by state formula funding, which is the mechanism with the strongest relationship with the poverty rate. State formula funding significantly increases in the poverty rate up to the threshold and then significantly decreases in the poverty rate after it, which is consistent with the hump shape in Figure 4. The other two mechanisms are not clearly related to the poverty rate.

The R^2 for the regressions without controls is less than 0.2. Funding allocations are largely determined by additional factors beyond poverty rates and state fixed effects.

The bottom two panels of Table 3 adds the other controls. Including the full set of controls increases the R^2, so that the regressions now explain a quarter of the variation in total funding. Including controls has mixed effects on the association between funding and poverty rate. Area-weighted formula funding is no longer significantly associated with the poverty rate and no longer has the hump shape seen in the raw data. That hump shape could be an artifact of states targeting funding based on other observables. Discretionary funding significantly increases in the poverty rate among non-disadvantage tracts, but whether the relationship continues or vanishes within disadvantage tracts is sensitive to the choice of weighting scheme. This suggests that, within states, discretionary funding may be progressively allocated.

The bottom panel of Figure 7 shows that conditional on the additional controls and poverty rate variables, FEMA damages are positively—and in the case of competitive funding, significantly—correlated with each type of funding. Funding agencies might be targeting recent experience of climate hazards even after controlling for other observables. Figure 6 showed that CIL damages and funding appear to be weakly correlated in the raw data, but we here see that any correlation with total funding vanishes once controlling for state fixed effects and the poverty rate.[32] This change likely reflects how state fixed effects largely absorb the strong north-south gradient in CIL

[32]However, CIL damages are positively correlated with funding under the discretionary mechanism.

damages seen in Figure 1. Adaptation funds do not clearly target equity or efficiency as measured by the CIL measure, but they do appear successful at targeting recent experience of climate hazards, especially through competitively funded projects.

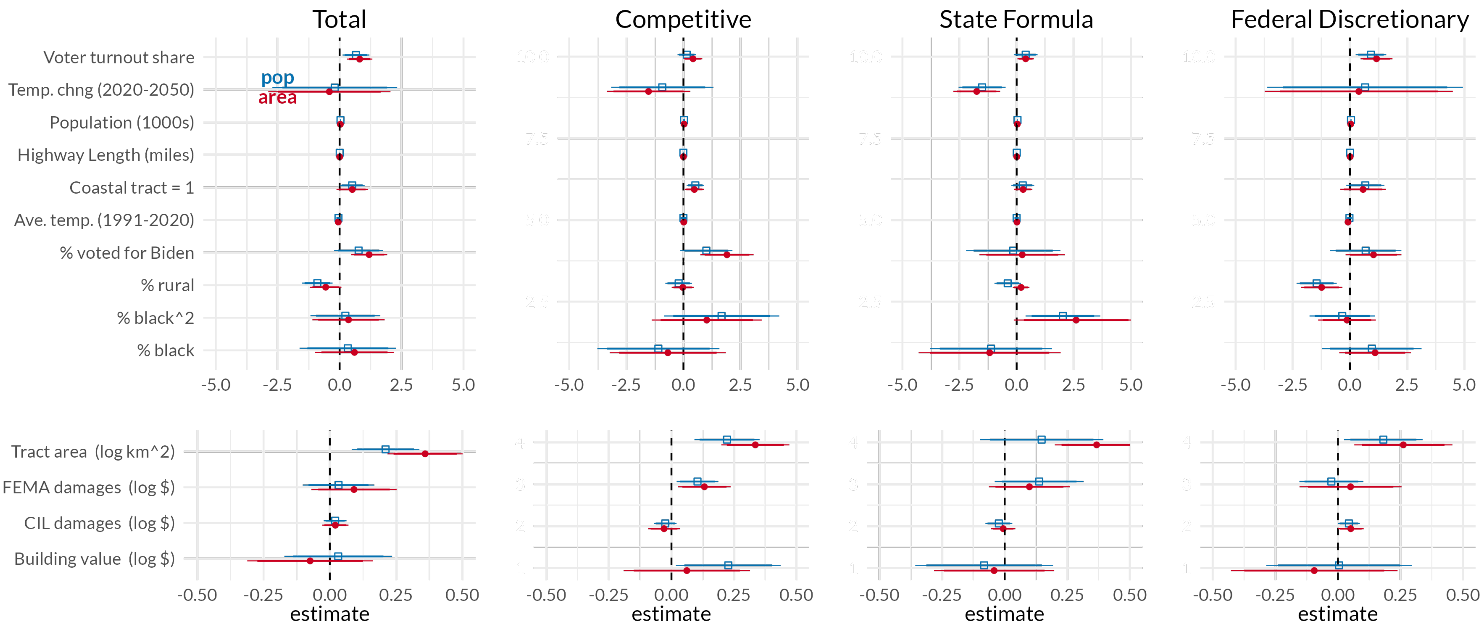
In Figure 7, we see that several covariates are significantly different from zero at the 5% level or better. Geographically larger, and less rural tracts receive more funding of all types. All else equal, tracts with a higher share voting for Biden and with more voter turnout receive more funding.

Table 3: Determinants of Adaptation Funding

		Mechanisms		
	Total	Competitive	Formula	Discretionary
No controls, area-weighted				
Percentile of poverty rate	0.252	−0.163	0.844***	−0.075
	(0.307)	(0.290)	(0.291)	(0.423)
P-tile ≥ 0.65	−0.112	0.132	−0.045	−0.275**
	(0.110)	(0.120)	(0.103)	(0.136)
(P-tile - 0.65) × (P-tile ≥ 0.65)	−0.751	0.389	−3.399***	0.826
	(0.531)	(0.678)	(0.772)	(0.661)
No controls, population-weighted				
Percentile of poverty rate	0.245	−0.043	0.758**	0.077
	(0.284)	(0.216)	(0.317)	(0.400)
P-tile ≥ 0.65	−0.104	0.050	0.004	−0.259**
	(0.088)	(0.081)	(0.066)	(0.119)
(P-tile - 0.65) × (P-tile ≥ 0.65)	−0.661	1.029**	−2.882***	0.217
	(0.469)	(0.493)	(0.811)	(0.546)
All controls, area-weighted				
Percentile of poverty rate	0.061	−0.379	−0.078	0.351***
	(0.156)	(0.417)	(0.268)	(0.132)
P-tile ≥ 0.65	−0.151*	0.068	−0.093	−0.273**
	(0.084)	(0.110)	(0.104)	(0.111)
(P-tile - 0.65) × (P-tile ≥ 0.65)	−0.181	1.341*	−1.196	−0.060
	(0.644)	(0.689)	(0.743)	(0.704)
All controls, population-weighted				
Percentile of poverty rate	0.604***	0.065	0.678***	0.721***
	(0.159)	(0.284)	(0.261)	(0.223)
P-tile ≥ 0.65	−0.106	0.015	−0.007	−0.255***
	(0.070)	(0.081)	(0.075)	(0.091)
(P-tile - 0.65) × (P-tile ≥ 0.65)	−1.170**	1.621***	−2.458***	−0.985**
	(0.462)	(0.536)	(0.541)	(0.448)
State FEs	yes	yes	yes	yes
Num. obs.	72010	70858	72010	72010
Pseudo R^2 no controls, area-weighted	0.140	0.186	0.163	0.182
Pseudo R^2 no controls, population-weighted	0.187	0.228	0.244	0.225
Pseudo R^2 all controls, area-weighted	0.242	0.314	0.314	0.231
Pseudo R^2 all controls, population-weighted	0.226	0.301	0.298	0.262

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Figure 7: Coefficients and confidence intervals in main specification



Note: These plots show the coefficient estimates and 90% (bold line) and 95% (thin line) confidence intervals for the controls in the full specificiation of the descriptive regressions. The red lines with a circle at the central estimate are area-weighted estimates, and the blue lines with squares at the central estimate are population weighted estimates. The coefficient estimates are grouped into level controls (top panel) and log controls (bottom panel) with different scales for ease of reading.

5 Counterfactual Funding Allocations

Our analysis has shown that there may be tension between funding adaptation projects in high-damage and disadvantaged tracts. It also shows that current funding does not target equity especially strongly. The evidence on how well funding targets efficiency is mixed: it does target damages as measured by our backward-looking FEMA metric of recent climate hazards, but it does not clearly target damages as measured by our forward-looking CIL damage metric.

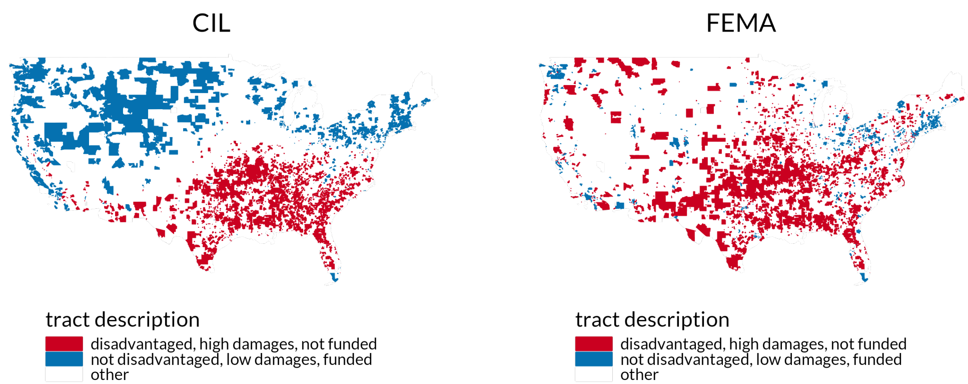
Figure 8 shows the geographical distribution of two kinds of tracts: (1) tracts that are funded but are neither disadvantaged nor particularly exposed to climate change, and (2) tracts that are not funded but are both disadvantaged and potentially particularly exposed to climate change, where we define particularly exposed as being above median for each damage measure. Reallocating funding from the former tracts to the latter tracts could improve both efficiency and equity. Such a reallocation would, in general, imply reducing funding to tracts in the North and West and increasing funding to tracts in the South or Southwest.

We now explore whether simple rules for reallocating funding to achieve equity objectives could improve efficiency outcomes. We consider four counterfactual funding allocations for achieving Justice40 by shifting funds from non-disadvantaged to disadvantaged tracts. The four counterfactuals illustrate the equity-efficiency tradeoff between an equity-based redistribution without concern for efficiency, a redistribution that considers the efficiency of where the funds are given to, a redistribution that considers the efficiency of where the funds are taken from, and a redistribution that considers the efficiency of both where funds are taken from and where they are given to. The first counterfactual takes funds equally across non-disadvantaged tracts and gives them equally to disadvantaged tracts. The second that takes funds equally from non-disadvantaged tracts, but sends them only to the most climate exposed disadvantaged tracts. The third that takes funds equally from the least climate exposed non-disadvantaged tracts and allocates them equally amongst disadvantaged tracts. The last counterfactual takes funds equally from the least climate exposed non-disadvantaged tracts and gives them to the most climate exposed disadvantaged tracts. All four counterfactuals precisely achieve the Justice40 target and plausibly improve equity in the funding allocation.

5.1 Counterfactual 1: Proportionally decrease funding to non-disadvantaged tracts to meet Justice40 goals

The first counterfactual reduces each non-disadvantaged tract's funding by an equal percentage and redistributes the additional funding equally across disadvantaged tracts. The total funds reallocated are just enough to meet the Justice40 target of 40% of funds going to disadvantaged tracts: each

Figure 8: Non-funded disadvantaged tracts with high climate damages, with funded non-disadvantaged tracts with low climate damages



Note: Tracts in red are disadvantaged tracts in the top third of climate damages overall, for the CIL measure (left panel) or FEMA measure (right panel), and which received no climate adaptation funding of any type. Tracts in blue are non-disadvantaged tracts in the lowest third of climate damages among all tracts that received positive climate adaptation funding. A small amount of tracts are missing CIL damages estimates due to missing per-capita income data.

funded non-disadvantaged tract loses 16.2% (12.7%) of its funding when we map funds to nearby tracts based on area (population), and each disadvantaged tract receives an extra $44,194 ($34,728) in funding. The top row of Figure 9 plots each Census tract's change in climate adaptation funding under this counterfactual against its estimated CIL and FEMA damages. In this figure, each point averages the change in funding over a given percentile of damages.

The reallocation of funds from non-disadvantaged to disadvantaged Census tracts increases funding in Census tracts that have low-to-medium CIL damages and generally decreases funding in places that have the highest CIL damages, regardless of whether we use population or area weighting to assign projects to tracts within a 10 km radius. FEMA damages tell a less clear story. Under area weighting, this reallocation again tends to decrease funding to the places with the highest damages. However, under population weighting, the reallocation does increase funding to some (but not all) of the most exposed damage percentiles.

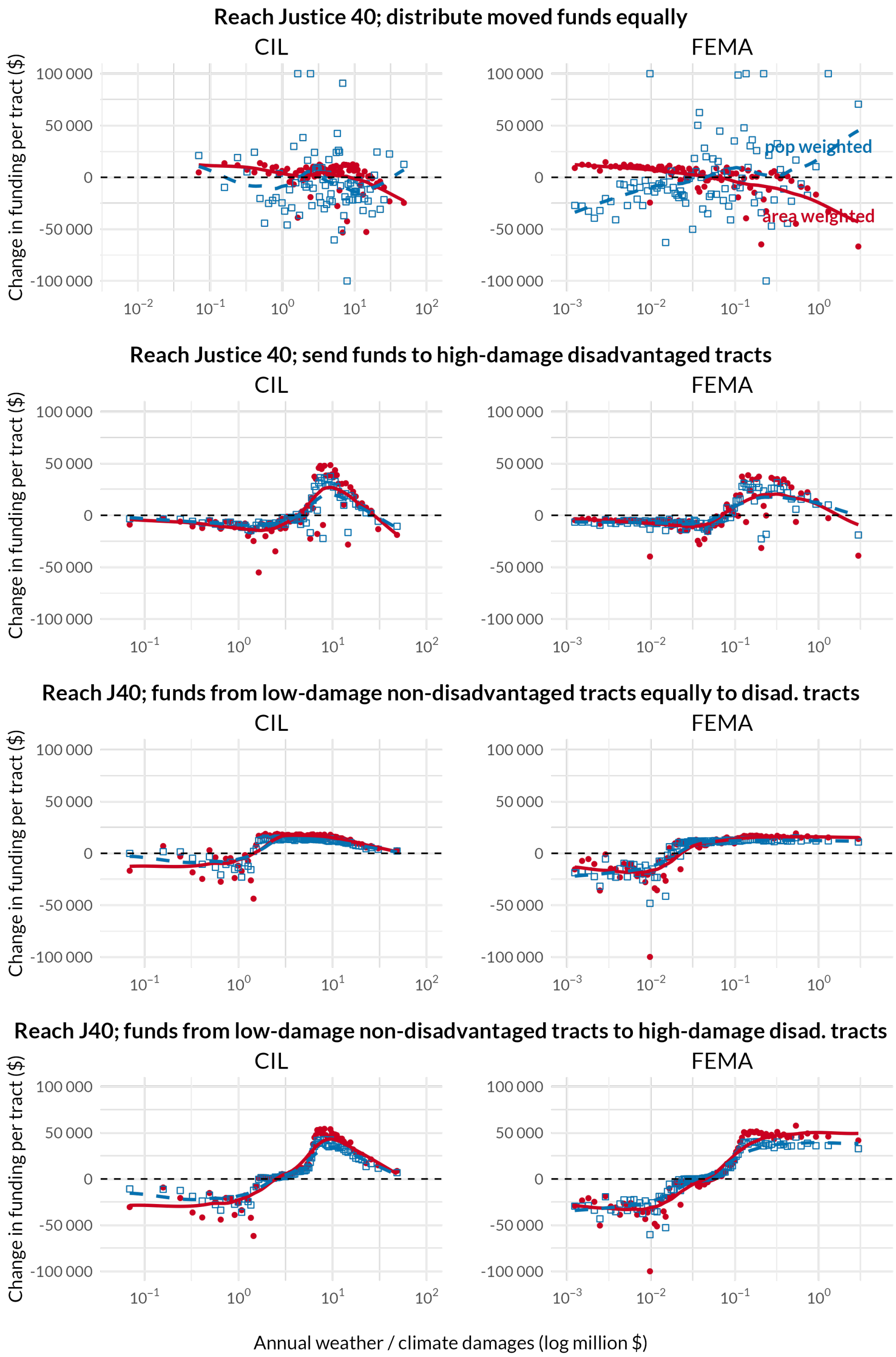
In sum, this counterfactual plausibly worsens efficiency with respect to the forward-looking CIL measure, suggesting a possible equity-efficiency tradeoff, but results are mixed for the backward-looking FEMA measure.

5.2 Counterfactual 2: Reach Justice40 by decreasing funding to non-disadvantaged tracts and redistribute funds among top damage tercile of disadvantaged tracts

The second counterfactual reduces non-disadvantaged tracts' funding by a constant percentage in order to reach Justice40 targets (as in the first counterfactual), and redistributes the funding removed from non-disadvantaged tracts equally to disadvantaged tracts in the top tercile of damages within each percentile of poverty rate. In this counterfactual, each disadvantaged tract in the top tercile of damages within its poverty rate percentile receives $132,783 ($104,318) in addition to its original allotment. This counterfactual targets funds toward disadvantaged tracts that are the most climate exposed and may benefit the most from adaptation funding, but does not consider the climate exposure of non-disadvantaged tracts from where funds are taken.

The second row of Figure 9 shows that this reallocation likely improves efficiency under either damage measure: funds are taken from low-to-medium damage Census tracts and given to high – but not the absolute highest – damage Census tracts. The first counterfactual showed that simple rules designed to increase equity could worsen the efficiency of adaptation funding, but the second counterfactual shows that more sophisticated mechanisms that redirect funding to the more exposed among the disadvantaged tracts may improve both equity and efficiency. One caveat is that the most exposed 1%-2% of tracts, typically non-disadvantaged tracts, may have a decrease in funding. Less funding goes to the most exposed tracts because in the actual funding allocation there are

Figure 9: Change in funding by CIL and FEMA damages, under counterfactual funding allocations



Note: These plots show a binscatter for the average changes in total funding for each percentile of damages, for each of four counterfactuals of funding allocations for both CIL and FEMA estimates of damages. We winsorize changes in funding to ±$100,000 for clarity in the plot. The solid lines are locally estimated best-fit lines for funding assumed to be distributed equally over area; the dashed lines are the analogous best-fit line for population-weighted funding.

substantially more non-disadvantaged tracts in the highest percentile of damages.[33]

5.3 Counterfactual 3: Reach Justice40 by decreasing funding to low-damage non-disadvantaged tracts and give funds equally to all disadvantaged tracts

The third counterfactual reduces funding to the lowest tercile of non-disadvantaged tracts' funding by a constant percentage in order to reach Justice40 targets, and then gives the funding removed from non-disadvantaged tracts equally to disadvantaged tracts. Under this counterfactual, disadvantaged tracts receive the same amount of funding as in the first counterfactual. However, under the FEMA damage metric and area-weighted funding, tracts in the lowest tercile of damages have their allotment reduced by 100%, while the second tercile's allocation is decreased by 4.9%.[34] For the FEMA damage metric and population-weighted funding, tracts in the lowest tercile have their allocation decreased by 57.3%. For CIL, the lowest tercile of non-disadvantaged tracts have a reduction of 55% for area-weighted funding and 41.3% for population-weighted funding.

In this counterfactual, although we do not target high damage disadvantaged Census tracts, we clearly see that on average, it shifts funding nearly uniformly from low damage to high damage Census tracts. Unlike the second counterfactual, the highest damage Census tracts, on average, receive an increase in adaptation funds.

5.4 Counterfactual 4: Reach Justice40 by decreasing funding to low-damage non-disadvantaged tracts and give funds to highest tercile of disadvantaged tracts

The fourth counterfactual reduces funding to the lowest tercile of non-disadvantaged tracts' funding by a constant percentage in order to reach Justice40 targets (as in the third counterfactual) and redistributes the funding equally to disadvantaged tracts in the top tercile of damages within each percentile of poverty rate (as in the second counterfactual). This funding distribution exhibits the most explicit efficiency targeting of any of the counterfactuals, while remaining a fairly simple mechanism.

The bottom row of Figure 9 shows that considering damages in where funds are taken from and where they are given to tends to concentrate the most funds in high damage Census tracts at the expense of significant declines in funding to the lowest damage Census tracts. Since the average tract in the data receives \$130,831 (\$135,987), a change in funding of ∼\$50,000 is large. These

[33] 14.4 times more by the CIL damage measure; 2.2 times more by the FEMA damage measure. For the CIL measure, more than half of the highest damage tracts are in Florida. For both measures, the average tract in the 99th percentile of damages are over 3 times more likely than average to be a coastal tract.

[34] Reallocating all the funds in the lowest tercile of non-disadvantaged Census tracts under area weighting and FEMA damages is insufficient to achieve Justice40 so we then reduce funds in the second tercile.

counterfactuals show that, on the margin, an equity-efficiency trade off may not exist under simple reallocation mechanisms that consider a Census tract's climate exposure.

6 Discussion: Designing Mechanisms for Achieving Equity Goals

The tension between equity and efficiency highlights the importance of designing funding mechanisms that navigate these tradeoffs while utilizing information about local needs and risks. The three adaptation funding mechanisms assessed here have different tradeoffs. Funds that are allocated by federal discretion may not take advantage of local knowledge, whereas state or local agencies may have a better sense of how to efficiently allocate dollars within a state.[35] Yet state agencies may not share a federal agency's equity (or electoral) goals,[36] and a competitive grant process may present an extra hurdle for higher-poverty locations that may have less institutional capacity.[37] In practice, we find that the competitive grant process tends to allocate the greatest share of funds to disadvantaged tracts and that state formula funding allocates a greater share of funds to disadvantaged tracts than does federal discretionary funding. Future work should consider the design of mechanisms to implement equity and efficiency goals and should further assess outcomes under these mechanisms. In particular, future work would benefit from obtaining data on the set of locations that applied for competitive funding but did not receive it.

Future work should also consider interactions among funding mechanisms. For instance, if competitive funding processes explicitly favor disadvantaged tracts, then either federal or state-level spending could emphasize less disadvantaged tracts. In this case, substitution across pots of money would undercut the equity objective. This kind of effect is consistent with our data, in which we see around half of competitive funding going to disadvantaged tracts but only a quarter of federal discretionary funding going to disadvantaged tracts, and with our statistical estimates, in which competitive funding increases in poverty rate among disadvantaged tracts whereas state formula funding decreases in poverty rate among disadvantaged tracts.

Our analysis also shows the importance of specifying equity objectives carefully. For instance, a funding mechanism could meet Justice40 criteria by directing nearly 40% of its funds to disadvantaged tracts while favoring lower-poverty tracts among the disadvantaged tracts. Specifying that all tracts above some threshold contribute equally to equity objectives will always permit such outcomes. An alternate approach would be to specify a measure of equity that prioritizes any

[35] See Levinson (2003) and Millimet (2014) for discussion of topics related to environmental federalism.

[36] To mitigate this principal-agent problem, White House Environmental Justice Advisory Council (2022) recommends disbursing funds in a staggered fashion that permits evaluation and/or developing penalties for noncompliance.

[37] Hansen et al. (2021) and White House Environmental Justice Advisory Council (2022) recommend ways to overcome application hurdles, and Walls et al. (2024) summarize current efforts at overcoming these hurdles.

poorer tract over any richer tract. Future work should consider tradeoffs among different types of metrics and ways to feasibly implement alternative metrics.

Finally, future work should develop methods for distinguishing value from spending. In particular, recent work has made progress in developing and estimating economic models that account for network linkages (e.g., Acemoglu et al., 2012; Carvalho and Tahbaz-Salehi, 2019), and recent work in environmental economics has accounted for transport of pollutants (e.g., Muller et al., 2011; Mendelsohn and Muller, 2013). Both effects could be critical to evaluating the efficiency and equity of adaptation spending. Much adaptation spending will protect supply chains and/or the environment in other locations. However, White House Environmental Justice Advisory Council (2022) emphasizes that spending, not total benefits, should be prioritized because spending itself directly benefits disadvantaged communities. Future work should quantify the tradeoffs between these various types of benefits from spending and assess whether a metric based on benefits could be sufficiently unambiguous to be noncontroversially implementable.

7 Conclusions

Our analysis suggests that adaptation funding is not strongly correlated with poverty rate measures of equity and is correlated with some damage measures of efficiency. This type of ex post program evaluation is possible because the equity criteria were clearly articulated by policymakers. Future analyses would benefit from a similar articulation of efficiency criteria. Moreover, our analysis is challenged because the available data make it difficult to ascertain precisely which Census tracts either receive or benefit from funding. Future analyses would benefit from more detailed and consistent data reporting, as also urged by Fencl et al. (2024).

Our analysis shows that equity targets may take work to achieve. The U.S. government has paid attention to the institutional barriers that may prevent disadvantaged tracts from applying for funding, and that work appears to have paid off. On the other hand, funding that is more purely discretionary on the parts of states and the federal government performs worse at achieving the equity target. It may be that competitive funding explicitly incorporates equity criteria into scoring systems that are not used when allocating discretionary funding.

Our analysis also suggests that equity-efficiency tradeoffs may bite at the margin. Simple rules that reallocate funding towards disadvantaged tracts may reduce resilience to climate change. However, equity and efficiency could both be improved if funding agencies can target places that are both disadvantaged and relatively exposed to climate change. Future work should examine these tradeoffs in more detail, with additional measures of climate exposure, in order to learn the degree to which funding needs to be properly targeted among disadvantaged tracts in order to mitigate—or even avoid—equity-efficiency tradeoffs.

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Appendix

A Example Programs for Each Funding Mechanism

A.1 State Formula: PROTECT

Promoting Resilient Operations for Transformative, Efficient, and Cost-Saving Transportation (PROTECT) is a program under the Fixing America's Surface Transportation (FAST) Act, implemented under the Obama administration (Federal Highway Administration, 2021).[38] The act funded highway repairs in 2016–2020. The act was renewed in October 2020 for one year, and then renewed again under the BIL, both with the same apportionment rule as the original act. The PROTECT Formula Program under the BIL is charged with improving the climate resilience of transportation infrastructure through the distribution of funding to state authorities. Examples of the type of resilience improvements include construction of tide gates to protect against sea level rise, and development of natural infrastructure that protects transportation infrastructure, among others.

Funding under PROTECT totals $7.3 billion from 2022–2026. Funds are allocated to states based on their share of total funding received from the Highway Trust Fund in 2021 with three caveats: (1) a state must get at least 95% of what it contributes to the Highway Trust Fund, (2) funding is over 2% more than what was allocated in 2021, and (3) funding allocations increase by at least 1% per year. The share of funding allocated to states in 2021 is determined by a federal highway funding formula that has not been changed since those implemented under the Safe, Accountable, Flexible, Efficient Transportation Equity Act of 2005. Factors in the formula include the state's share of lane-miles, vehicle miles traveled, and fatalities on federal aid highways, as well as population.

The FAST act distributes the set formula of transportation funding to each state, split among several programs. PROTECT gets 2.91% of the remaining highway funding after states allocate about 8.5% of funding to the Congestion Mitigation and Air Quality Improvement Program, National Highway Freight Program, and the Metropolitan Planning Program. This leaves approximately $1.4 billion per year to the PROTECT program (Federal Highway Administration, 2021).

States have substantial discretion in how they spend federal highway dollars. State governments decide which projects to undertake, and get reimbursed by the federal government for projects that meet federal eligibility requirements under the various programs. Usually, the federal government is allowed to reimburse up to 80% of the project. About 95% of federal highway dollars are used on capital projects, whereas state funds tend to be for operations and maintenance (Congressional Budget Office, 2023).

[38] See U.S. Code Title 23, Chapter 1, Section 104 for additional details.

A.2 Competitive: National Coastal Resilience Fund

The National Coastal Resilience Fund (NCRF) is a competitive grant funding mechanism aimed at restoring or improving natural infrastructure to protect coastal communities and ecosystems from coastal hazards like flooding and storms (National Fish and Wildlife Foundation, 2023a). The NCRF is primarily funded by the National Oceanic and Atmospheric Administration and jointly operated with the National Fish and Wildlife Foundation. In 2023 the NCRF allocated nearly $150 million in awards.

The goal of the NCRF is to fund natural infrastructure investments in projects like coastal marsh restoration, dune rebuilding, and living reef development. It prioritizes projects that are able to be completed quickly and start generating benefits as well as projects that benefit underserved communities. Projects are evaluated using the Regional Coastal Resilience Assessments which identifies lands that have the greatest benefits from natural coastal infrastructure investments (National Fish and Wildlife Foundation, 2023b).

A.3 Federal Discretionary: Hazardous Fuels Management

The Hazardous Fuels Management program allocates funds to the US Forest Service for wildfire mitigation and the development of resilient forests through the reduction of flammable vegetation (USDA Office of the Inspector General, 2023). Total funding is approximately $100 million per year from 2022–2026.

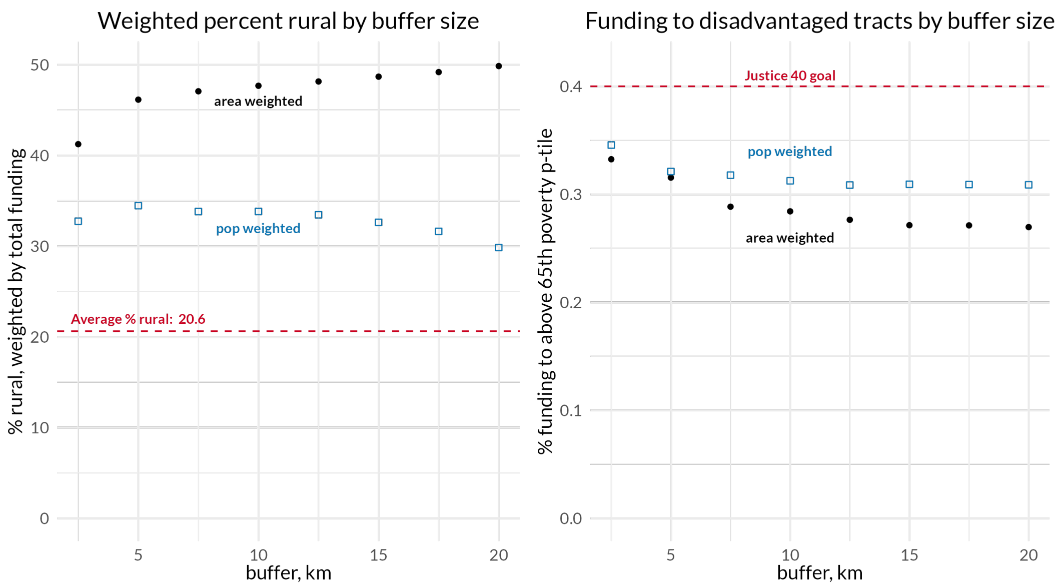
The program funds several different activities hazardous fuels activities to reduce wildfire risk such as forest thinning and timber harvesting, prescribed fires, and installation of fuel breaks in the natural habitat. In addition, grants are also awarded to incentivize the use of flammable biomass through, for example, increasing wood manufacturing capacity and further developing wood energy markets. Funds are also allocated for projects under the Tribal Forest Protection Act of 2004, which is responsible for funding projects to protect tribal lands and communities from wildfire, insects, and disease. Approximately 45% of program funds have been used on hazardous fuels activities and 8% has been used for Tribal Forest Protection Act purposes.

B Sensitivity Checks

B.1 Sensitivity to assumed buffer size

In our main analysis, we use a 10km buffer around the approximately 900 projects with only point locations because 10km is roughly the size of a town. We now assess sensitivity of our results to buffer size.

Figure B1: Change in descriptive statistics with buffer size



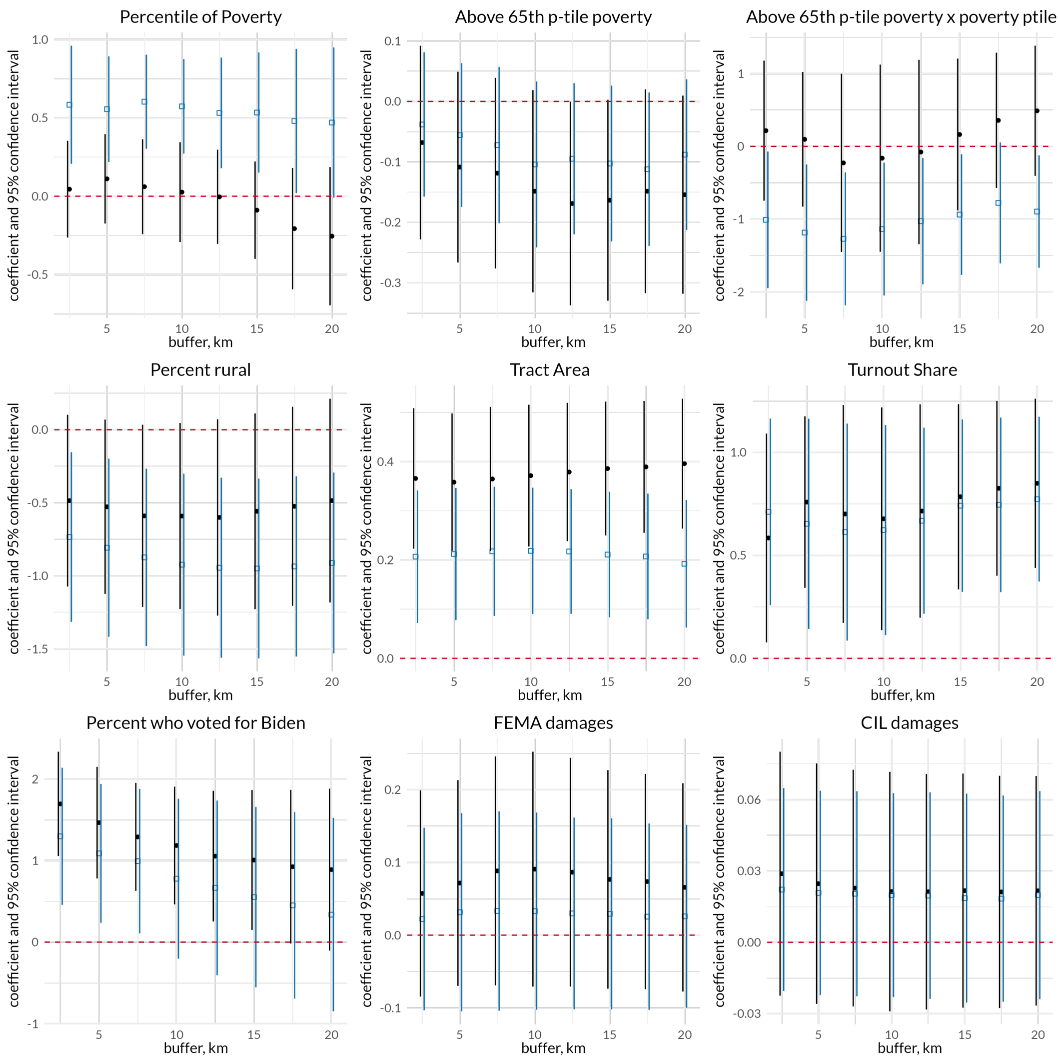
Note: In the left panel, we calculate the average of tracts' percent rural, weighted by dollars of funding to each tract, as assumed to be distributed with each funding weighting scheme (equal across area, weighted by population) and each buffer size around the $\sim$ 900 awards with only point locations. The horizontal line shows the average percent rural across all tracts in the 50 United States. The right panel shows the percent of funding to disadvantaged tracts that each buffer size around point locations implies.

One might be concerned that a given buffer size makes more rural tracts appear to receive more funding because they completely contain the buffer around some point and so absorb all of the funding assigned to that point. The left panel of Figure B1 plots the rural share for the average dollar of funding. This value is sensitive to buffer size but is always well above the national average rural share, reflecting a consistent rural bias in funding.

The right panel assesses whether the value of funding flowing to disadvantaged tracts is sensitive to the assumed buffer size. Funding to disadvantaged tracts does fall sharply as the buffer size increases. In fact, the Justice40 target can be met if we use both a very small buffer and a rule that assigns funding to tracts based on population shares in the buffer. The Justice40 targets is not attained under other assumptions.

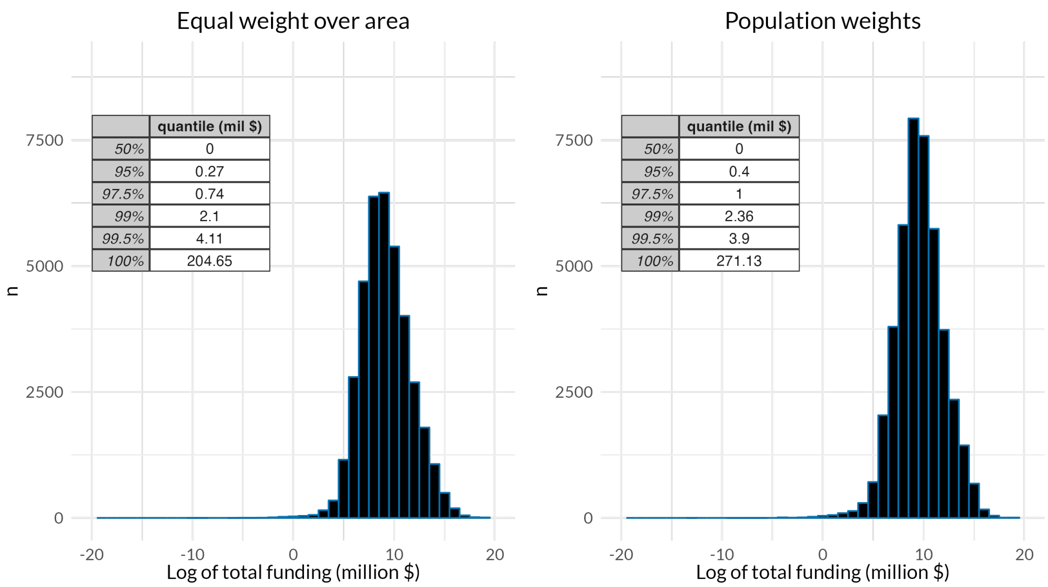
For Figure B2, we run our main regression specification for various buffer sizes and plot the coefficients. Coefficients are insensitive to buffer size: we can always reject that they are statistically different.

Figure B2: Coefficients by buffer size, funding weights



Note: We show coefficient estimates and 95% confidence intervals for total funding on each of the variables listed at the tops of plots, in our main specification with all controls. Blue squares show the central estimate for the assumption of population-weighted funding, while black dots show the central estimate for funding allocated equally over space. A horizontal dashed line is plotted at zero for reference.

Figure B3: Un-winsorized Census tract funding distribution

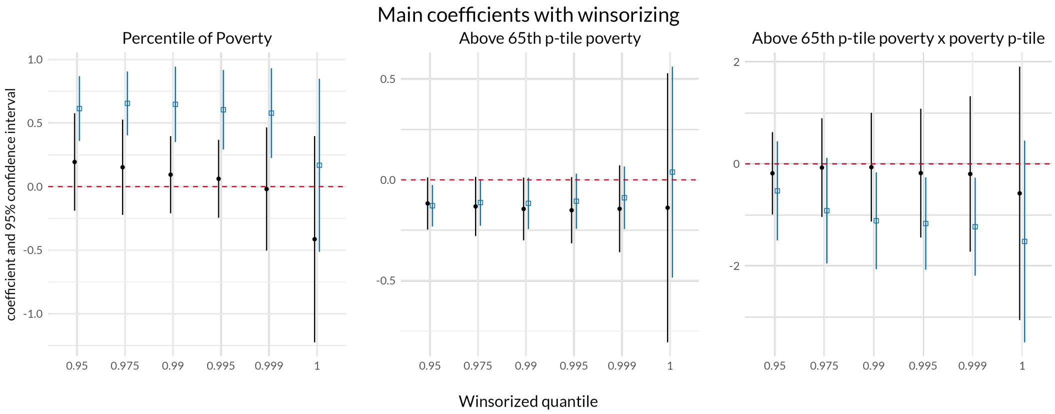


B.2 Sensitivity to winsorizing

Figure B3 shows the distribution of funding levels across census tracts along with the values at particular percentiles. The distributions appear to be lognormal, however there are a handful of Census tracts receiving orders of magnitude more funding than the others. Because of this, we winsorize our data at the 99.5th percentile.

In Figure B4, we show how our main coefficients change as we winsorize funding data. The values of the coefficients with no winsorizing (at winsorized quantile = 1) are slightly different from the trend of coefficients with winsorizing, which are comparatively stable. The plot suggests that outliers may drive our results in the absence of winsorizing. We choose to winsorize our data conservatively, at the 99.5th percentile. We can see that choosing a lower or higher percentile would not drastically change our main coefficients.

Figure B4: Main coefficients under different winsorization of funding



Note: We show coefficient estimates and 95% confidence intervals for total funding on each of the variables listed at the tops of plots, in our main specification with all controls. Blue squares show the central estimate for the assumption of population-weighted funding, while black dots show the central estimate for area-weighted funding. A horizontal dashed line is plotted at zero for reference. The x-axis shows the quantile of funding where the data is winsorized at. A winsorized quantile of 1 is equivalent to no winsorizing.

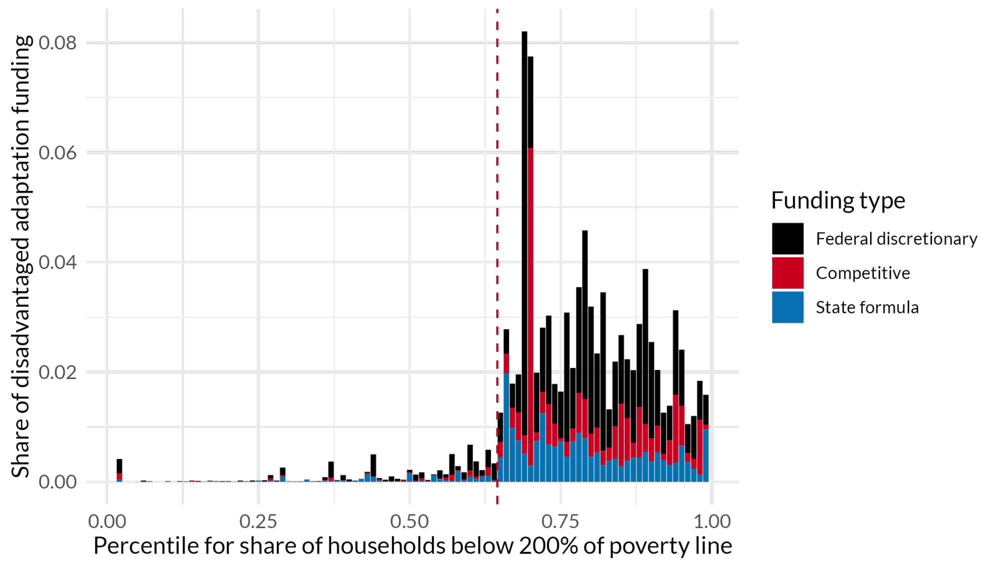
C Supporting Results

C.1 Most funding to disadvantaged tracts goes to lower-poverty tracts

94% of tracts above the 65th percentile of poverty qualify as disadvantaged according to the full Justice40 disadvantaged definition. Therefore, Justice40 applies equally to a broad group of tracts of various levels of burden and poverty. We assess whether funding is targeted to certain characteristics within disadvantaged tracts, first by poverty rate percentile.

Figure C5 shows what percentage of adaptation funding to disadvantaged tracts goes to each poverty rate percentile. 38.3% of tracts are either disadvantaged by the Justice40 definition or are above the 65th percentile of the poverty rate. Of these tracts, 84.3% fall into both categories; 10.6% are disadvantaged but below the 65th percentile of the poverty rate, and 5% are above the 65th percentile and not considered disadvantaged. Of the funding that goes to disadvantaged tracts and tracts above the 65th percentile, 92.6% goes to tracts in both categories. Only 5.3% goes to disadvantaged tracts below the 65th percentile of the poverty rate, and 2% goes to non-disadvantaged tracts above the 65th percentile of the poverty rate. More funding goes to the lower-poverty half of qualifying tracts, even if this pattern partly reflects outliers in the dataset. In fact, of the 22 tracts that received more than 50 million dollars, only 6 were considered disadvantaged, all were below the 85th percentile of the poverty rate, and 2 were at the 65% cutoff. We do not remove outliers in the dataset because they may reflect intentional targeting of tracts to meet Justice40.

Figure C5: Histogram of funding to disadvantaged tracts, by poverty rate



C.2 Can, and does Justice40 funding target race?

The Biden Administration has deliberately omitted race from being a determinant of disadvantaged status, in order to protect Justice40 from a court challenge (Friedman, 2022). However, failing to include race could limit Justice40's ability to address environmental justice; some studies have found race to be a more important determinant of the incidence of environmental injustice than income and poverty (see, for example, Bullard et al. (2008), Cushing et al. (2015) and Mohai and Bryant (2019)).

Here we explore if and how funding has been distributed with regard to race. The top left panel of figure C6 shows that Justice40's poverty measure is highly correlated with race, with the average percent non-white or black increasing steeply after the disadvantaged cutoff. Without targeting race explicitly, targeting poverty may result in a correlation between race and funding. Moreover, even without explicit targeting of race, we may see a positive correlation because percent black and percentile non-white population correlates with the other factors determining the Justice40 disadvantaged status as reported by the Climate and Economic Justice Screening Tool, especially legacy pollution exposure.

The next three figures explore whether adaptation funding goes disproportionately to Census tracts with larger non-white or black populations, conditional on poverty. We do so by binscattering funding against percent non-white and percent black, residualizing by the poverty rate measure. The plots show little evidence of funding going to tracts with a higher proportion of non-white residents, after controlling for poverty rate. We do see a higher proportion of funding going to tracts with a higher black population after controlling for poverty, which is driven exclusively by federal discretionary funding.

C.3 Results split by states with environmental justice boards

State formula funding presents special obstacles to a federal equity goal because states have discretion about how to allocate funds within their borders but may not share either the broader equity goal or the definition of the equity goal. 14 states, covering 46.2% of Census tracts, have either a task force, commission, or office that advises the state government on environmental justice concerns. To test whether funding patterns are different in states with these boards, we estimate the following equation:

$$y_{is}^j = \alpha_1^j P_{is} + \alpha_2^j D_{is} + \alpha_3^j (P_{is} - 0.65) D_{is} + \alpha_4^j D_{is} EJ_s + \alpha_5^j (P_{is} - 0.65) D_{is} EJ_s + \beta^j X_{is} + \eta_s^j + \epsilon_{is}^j.$$

EJ_s is an indicator for whether state s has an environmental justice board. The coefficients α_4^j and α_5^j tell us whether the jump in funding at the 65th percentile poverty rate threshold and whether the correlation between poverty rate and funding beyond the threshold differ in states with environmental justice boards.

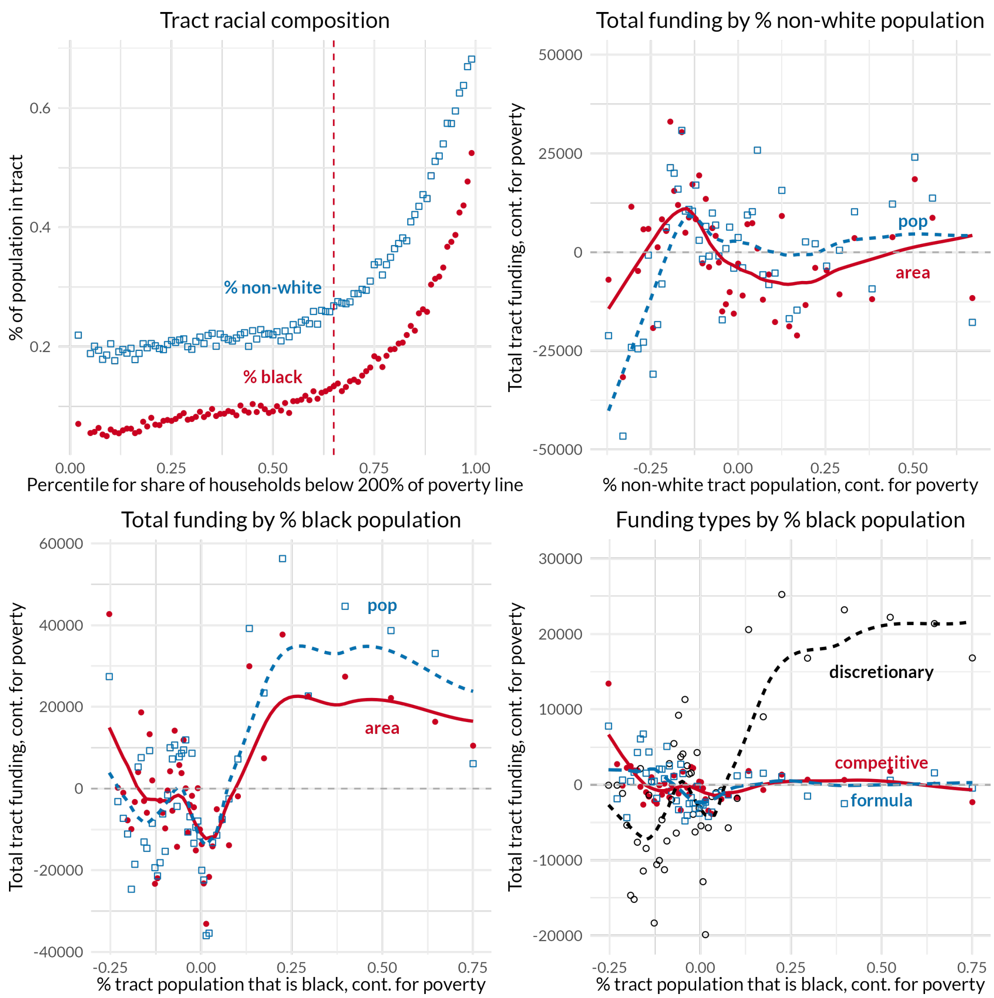
Table C1 reports the results. States with environmental justice boards do not appear to direct more formula funding to Census tracts near the threshold and direct *less* formula and competitive funding to the disadvantaged tracts with the highest poverty rates. This is surprising, since one might expect environmental justice boards to be most important for directing state formula funding. Of course, states choose whether to form such boards. As a result, states with such boards could have particular preferences and/or characteristics that affect how each mechanism allocates funding to disadvantaged tracts.

Table C1: Determinants of adaptation funding, split by states that have environmental justice boards

		Mechanisms		
	Total	Competitive	Formula	Discretionary
No controls, area-weighted				
Percentile of poverty rate	0.173	−0.622	0.773**	−0.251
	(0.239)	(0.527)	(0.313)	(0.344)
P-tile $\geq$ 0.65	−0.072	0.161	−0.002	−0.227
	(0.111)	(0.171)	(0.098)	(0.188)
(P-tile - 0.65) $\times$ (P-tile $\geq$ 0.65)	−0.729	1.863**	−3.232***	0.971
	(0.765)	(0.757)	(0.895)	(1.187)
(P-tile $\geq$ 0.65) $\times$ EJ board = 1	−0.090	0.014	−0.170	−0.082
	(0.227)	(0.236)	(0.273)	(0.258)
(P-tile $\geq$ 0.65) $\times$ (P-tile - 0.65) $\times$ (EJ board = 1)	−0.001	−2.975***	−1.149	−0.195
	(1.018)	(0.940)	(1.524)	(1.328)
All controls, area-weighted				
Percentile of poverty rate	−0.222	−1.072	−0.301	0.084
	(0.288)	(0.658)	(0.268)	(0.368)
P-tile $\geq$ 0.65	−0.121	0.074	−0.043	−0.216
	(0.108)	(0.190)	(0.102)	(0.175)
(P-tile - 0.65) $\times$ (P-tile $\geq$ 0.65)	−0.185	2.378**	−0.905	0.182
	(0.905)	(1.002)	(0.749)	(1.213)
(P-tile $\geq$ 0.65) $\times$ EJ board = 1	−0.058	0.042	−0.167	−0.093
	(0.225)	(0.233)	(0.226)	(0.268)
(P-tile $\geq$ 0.65) $\times$ (P-tile - 0.65) $\times$ (EJ board = 1)	0.491	−1.598*	−1.203	−0.339
	(0.984)	(0.896)	(1.324)	(1.480)
All controls, population-weighted				
Percentile of poverty rate	0.378	−0.550	0.499**	0.613*
	(0.279)	(0.699)	(0.238)	(0.368)
P-tile $\geq$ 0.65	−0.052	0.077	−0.010	−0.215
	(0.081)	(0.184)	(0.076)	(0.139)
(P-tile - 0.65) $\times$ (P-tile $\geq$ 0.65)	−1.368**	2.467***	−2.133***	−1.372*
	(0.563)	(0.894)	(0.524)	(0.832)
(P-tile $\geq$ 0.65) $\times$ EJ board = 1	−0.120	−0.065	0.081	−0.073
	(0.160)	(0.199)	(0.189)	(0.217)
(P-tile $\geq$ 0.65) $\times$ (P-tile - 0.65) $\times$ (EJ board = 1)	0.819	−1.270	−1.358	0.829
	(0.681)	(0.964)	(1.656)	(0.986)
State FEs	yes	yes	yes	yes
Num. obs.	72010	70858	72010	72010
Pseudo R^2 no controls, area-weighted	0.140	0.187	0.163	0.182
Pseudo R^2 all controls, area-weighted	0.242	0.315	0.315	0.231
Pseudo R^2 all controls, population-weighted	0.227	0.301	0.298	0.262

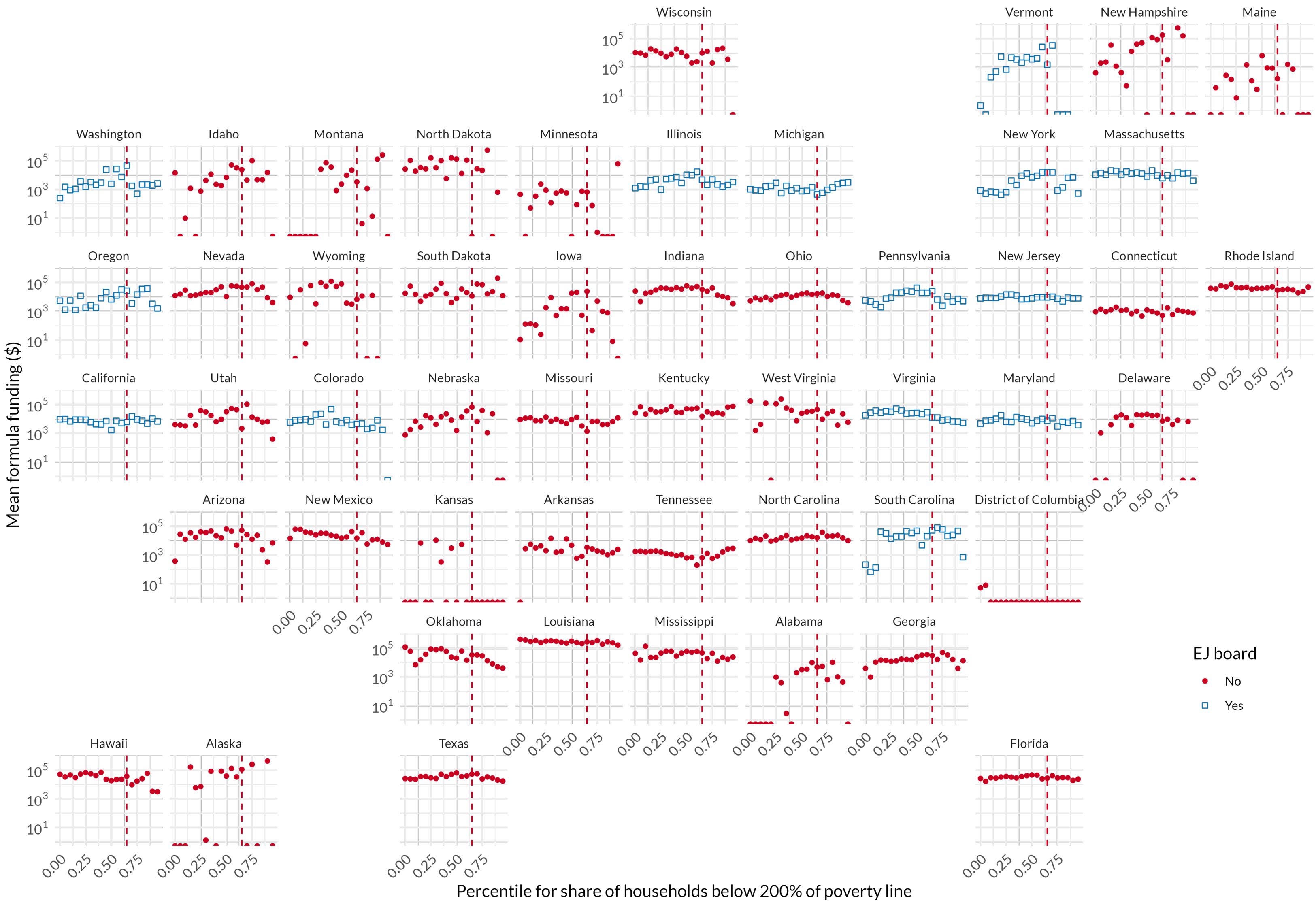
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Figure C6: Funding to tracts by racial composition, controlling for poverty



Note: The top left plot shows a binscatter for the average percent of people in a tract who identify as either black or non-white, for each percentile for the share of households below 200% of the poverty line. The top right plot shows a binscatter for how total funding varies by the percent of the population that is non-white in each tract, for both our area and population-weighted funding measure. We residualize the total funding and percent non-white by the poverty rate percentile measure used throughout the paper. The bottom two plots show similar residualized binscatters, where tracts are binned by the percent of the population that is black. The bottom right plot splits total funding into the three mechanisms. We winsorize total funding to the .995 percentile before binning. The lines are locally estimated best-fit lines.

Figure C7: Formula funding for tracts in each poverty bin, population-weighted



Note: Each point is the average population-weighted funding for each percentile of the Census tract distribution of the share of households below 200% of the poverty line, for each state. The vertical dashed line corresponds to the 65th percentile which is the threshold for meeting the poverty rate criterion for being considered disadvantaged. Blue squares denote states that have environmental justice boards and red dots denote states that do not. Binscatter percentiles are calculated using the national poverty rate distribution. Zero values indicate either no funding was allocated to Census tracts with that poverty rate percentile or that the state does not have any Census tracts falling into that poverty rate percentile.

D Per Capita Funding Results

In this section we show results for funding per capita by tract, instead of total funding by tract.

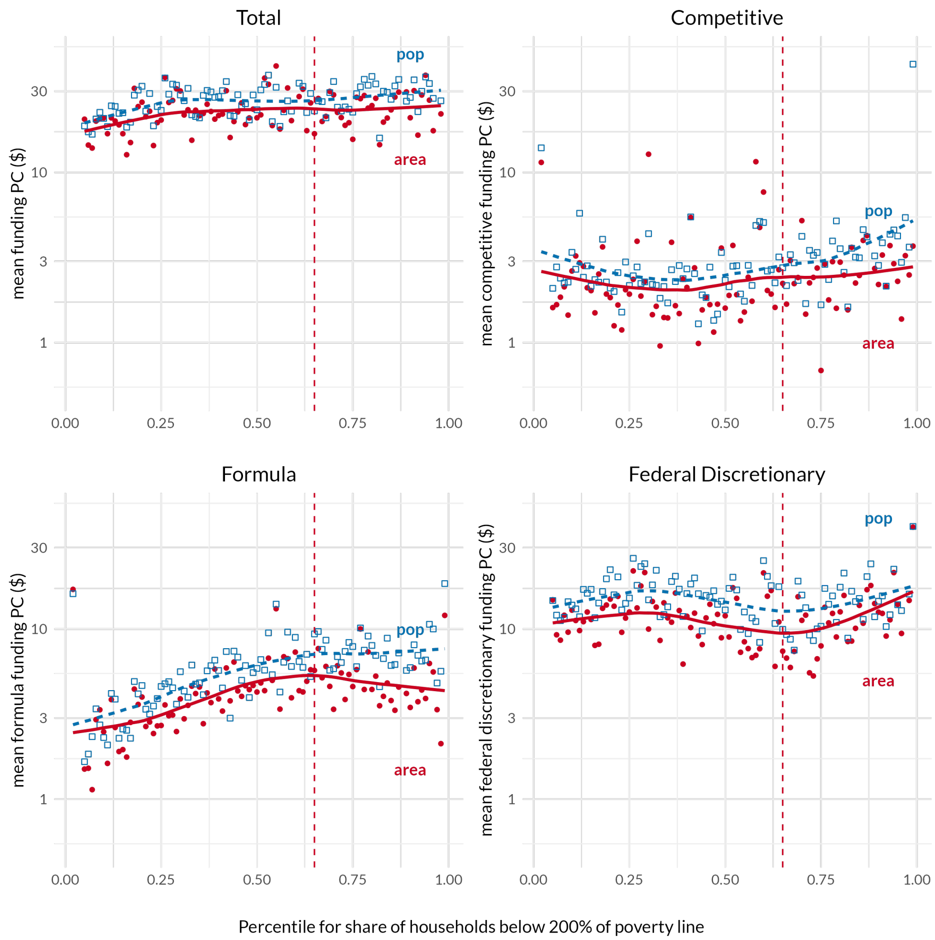
Figure D8 binscatters funding per capita against the poverty rate. Compared to Figure 4, per capita funding may be allocated slightly more progressively than total funding. The decline of formula funding above the poverty rate threshold also attenuates or vanishes when funding is in per capita terms.

Figure D9 shows that state formula funding per capita follows similar patterns to total funding.

Figure D10 shows that putting funding into per capita terms changes the direction of the association between funding and damages for the forward-looking CIL damage measure but not the backward-looking FEMA damage measure.

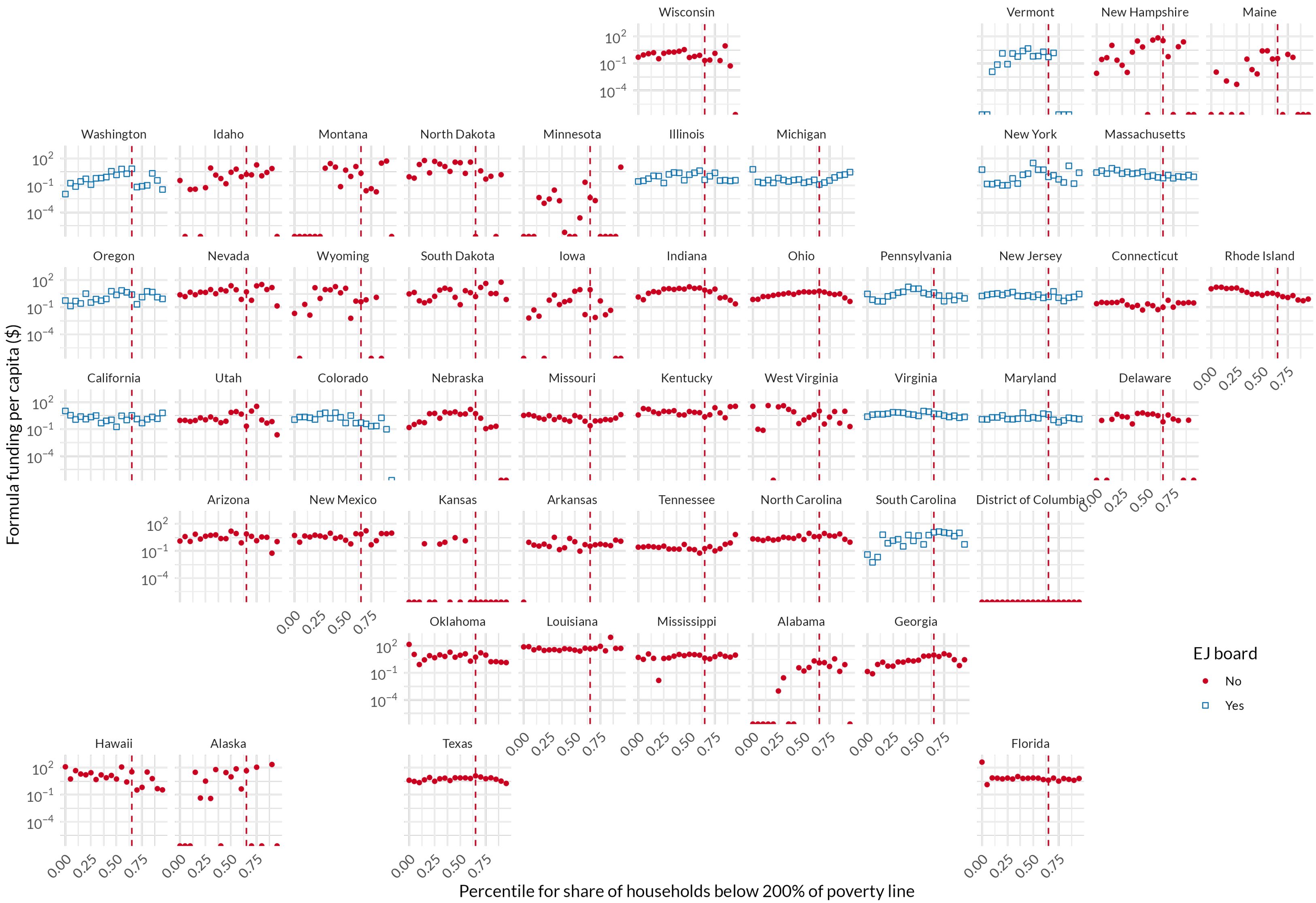
Table D2 replicates Table 3 but for per capita funding. Without controls but conditional on state fixed effects, total funding per capita has a v-shaped relationship with the poverty rate. All three funding mechanisms have the same pattern with varying statistical significance. The inclusion of controls attenuates the estimates, however the v-shaped relationship remains for total funding, although it is statistically insignificant. For the individual funding mechanisms, the inclusion of controls may qualitatively change the relationship. For example, population-weighted discretionary funding is monotonically declining in the poverty rate while population-weighted formula funding is hump-shaped.

Figure D8: Per capita adaptation funding, by poverty rate percentile and funding mechanism



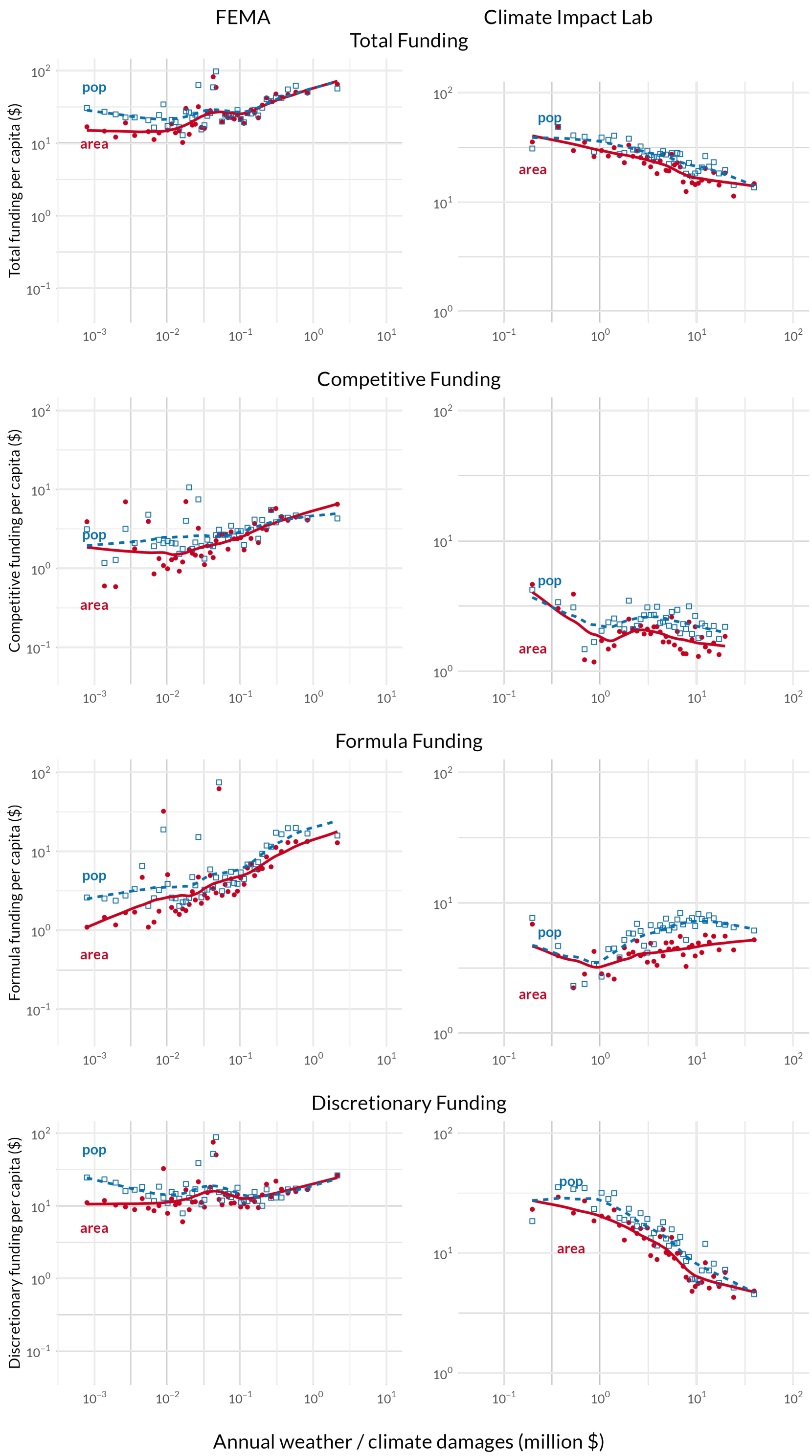
Note: Each point is the average per capita funding for each percentile of the Census tract distribution of the share of households below 200% of the poverty line. Before taking the average we winsorize Census tract funding levels to the 99.5th percentile. The solid lines are locally estimated best-fit lines for funding assumed to be distributed equally over area; the dashed lines are the analogous best-fit line for population-weighted funding. The vertical dashed line corresponds to the 65th percentile, which is the threshold for meeting the poverty rate criterion for being considered disadvantaged.

Figure D9: Per capita formula funding for tracts in each poverty bin, area weighted



Note: Each point is the average per capita area-weighted funding for each percentile of the Census tract distribution of the share of households below 200% of the poverty line, for each state. The vertical dashed line corresponds to the 65th percentile which is the threshold for meeting the poverty rate criterion for being considered disadvantaged. Blue squares denote states that have environmental justice boards and red dots denote states that do not. Binscatter percentiles are calculated using the national poverty rate distribution. Zero values indicate either no funding was allocated to Census tracts with that poverty rate percentile or that the state does not have any Census tracts falling into that poverty rate percentile.

Figure D10: Per capita funding mechanisms by damage components



Note: Each point is the the average per capita Census tract funding plotted against FEMA and CIL damages. Before taking the average we winsorize Census tract funding levels to the 99.5th percentile. The FEMA measures represents current expectations of weather-related hazards for six climate-related disasters. The CIL measure represents one version of expected future (2080–2090) damages in a high-emission scenario. For the lowest damage percentiles, the CIL measure estimates no damages (cold states are better off under climate change). We exclude these lowest bins from the plot. The solid lines are locally estimated best-fit lines for funding assumed to be distributed equally over area; the dashed lines are the analogous best-fit line for population-weighted funding.

Table D2: Determinants of Per Capita Adaptation Funding

		Mechanisms		
	Total	Competitive	Formula	Discretionary
No controls, area-weighted				
Percentile of poverty rate	-2.361^{*}	-0.923	-1.694	-2.638^{**}
	(1.270)	(1.681)	(1.616)	(1.216)
P-tile $\geq$ 0.65	0.460	0.791	0.455	0.061
	(0.383)	(0.978)	(0.369)	(0.400)
(P-tile - 0.65) $\times$ (P-tile $\geq$ 0.65)	6.076^{***}	6.389^{***}	3.202	7.089^{***}
	(1.653)	(2.430)	(2.157)	(1.783)
No controls, population-weighted				
Percentile of poverty rate	-1.495^{**}	-1.679	-1.069	-1.947^{**}
	(0.595)	(1.481)	(0.889)	(0.882)
P-tile $\geq$ 0.65	0.247	1.157	0.382^{**}	-0.444
	(0.374)	(1.074)	(0.185)	(0.341)
(P-tile - 0.65) $\times$ (P-tile $\geq$ 0.65)	6.879^{***}	7.964^{***}	2.543	9.200^{**}
	(1.958)	(1.633)	(1.587)	(3.738)
All controls, area-weighted				
Percentile of poverty rate	-1.018	-0.038	0.557	-2.303^{***}
	(0.762)	(1.077)	(0.507)	(0.893)
P-tile $\geq$ 0.65	-0.033	-0.198	-0.172	0.125
	(0.139)	(0.330)	(0.140)	(0.221)
(P-tile - 0.65) $\times$ (P-tile $\geq$ 0.65)	2.590^{**}	0.315	0.016	2.586^{*}
	(1.203)	(1.416)	(0.766)	(1.565)
All controls, population-weighted				
Percentile of poverty rate	-0.342	-0.442	0.874^{*}	-1.594^{*}
	(0.764)	(0.623)	(0.451)	(0.822)
P-tile $\geq$ 0.65	0.218	0.042	-0.057	0.203
	(0.185)	(0.278)	(0.090)	(0.229)
(P-tile - 0.65) $\times$ (P-tile $\geq$ 0.65)	1.414	1.796^{**}	-1.020	0.653
	(0.949)	(0.843)	(0.642)	(0.812)
State FEs	yes	yes	yes	yes
Num. obs.	72010	70858	72010	72010
Pseudo R^2 no controls, area-weighted	0.136	0.229	0.198	0.166
Pseudo R^2 no controls, population-weighted	0.200	0.259	0.284	0.234
Pseudo R^2 all controls, area-weighted	0.511	0.422	0.627	0.369
Pseudo R^2 all controls, population-weighted	0.474	0.358	0.603	0.354

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$